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Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment

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Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment

by

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We hereby certify that this dissertation, submitted by Wendy Tu, conforms to acceptable standards and is fully adequate in scope and quality to fulfill the dissertation requirements for the degree of Doctor of Philosophy.

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An Abstract of a Dissertation Submitted to Nova Southeastern University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

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Wendy Tu
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Difficulties in learning and understanding statistics in college education have led to a reform movement in statistics education in the early 1990s. Although much work has been done, there is more work that needs to be done in statistics education. The progress depends on how well the educators bring interesting real-life data into the classroom.

The goal was to understand how course design based on First Principles of Instruction could facilitate tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. An embedded single descriptive case design was employed to investigate how integrating technology and real data into a tertiary level statistics course would affect students' statistical literacy, reasoning, and thinking. Data including online assignment postings, online discussions, online peer evaluations, a comprehensive assessment, and open-ended interviews were analyzed to understand how the implementation of First Principles of Instruction affected a student's conceptual understanding in a tertiary level introductory statistics course. In addition, the teaching and learning quality (TALQ) survey was administered to evaluate the teaching and learning quality of the designed instruction from the student's perspective.

Results from both quantitative and qualitative data analyses indicate that the course designed following Merrill's First Principles of Instruction contributes to a positive overall effectiveness of promoting students' conceptual understanding in terms of literacy, reasoning, and thinking statistically. However, students' statistical literacy, specifically, the understanding of statistical terminology did not develop to a satisfactory level as expected.

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Chapter 1

Introduction

Background

For many students, statistics has a reputation for being boring, unappetizing, and the worst experience in college education (Brown & Kass, 2009; Hogg, 1992). Difficulties in learning and understanding statistics make it a notorious subject in college education. In 1990, a workshop on statistics education addressing these problems took place in Iowa (Hogg). The workshop became the first step of the reform movement in statistics education. Subsequently, Cobb (1992) proposed recommendations on the following three areas in teaching statistics: emphasize statistical thinking, use more data and concepts, and foster active learning. Cobb's proposal was later expanded and formed into the basis of the GAISE Project (Guidelines for Assessment and Instruction in Statistics Education) (American Statistical Association, 2005; Franklin & Garfield, 2006). In the GAISE Project, the following six recommendations for teaching introductory statistics were proposed:

- Emphasize statistical literacy and develop statistical thinking.
- Use real data.
- Stress conceptual understanding rather than mere knowledge of procedures.
- Foster active learning in the classroom.
- Use technology for developing concepts and analyzing data.
- Use assessments to improve and evaluate student learning.

In December 2005, The American Mathematical Association of Two-Year Colleges (AMATYC) endorsed these recommendations. What is missing is prescriptive guidance on how to effectively design an introductory statistics course that incorporates these recommendations.

Statistics Education

Statistical literacy, statistical reasoning, and statistical thinking are the three overarching goals of statistics instruction (delMas, 2002). While many papers and texts use the terms interchangeably without giving formal definitions, the fundamental idea is to emphasize the importance of conceptual understanding and to move away from the traditional way of solving problems merely for a numerical solution (Chance, 2002). Rumsey (2002) explains the phrase "statistical literacy" as basic statistical competence that involves five components: data awareness, an understanding of certain basic statistical concepts and terminology, knowledge of the basics of collecting data and generating descriptive statistics, basic interpretation skills, and basic communication skills (p.9). Statistical reasoning is "the way people reason with statistical ideas and make sense of statistical information" (Garfield & Gal, 1999, p.1). Reasoning means understanding statistical processes and being able to interpret statistical results (Garfield, 2002). Finally, the term "statistical thinking" goes beyond "literacy" and "reasoning." A statistical thinker views the entire statistical process as a whole and asks "why" to question and investigate the issues through the context of a problem (Chance, 2002). To emphasize statistical literacy, Gould (2010) claims that learners need to be able to analyze data with the context, which echoes Cobb and Moore's (as cited in Gould) definition of data as "numbers with a context." Early exposure to solving data with real

and interesting contextual questions motivates students and could create a more relevant course (Gould; Nolan & Temple Lang, 2009).

Due to advanced modern technology, today's students are exposed to data directly and regularly on a daily basis, even before their first experience with introductory statistics courses (Gould, 2010). As opposed to static and abstract data that are typically contained in textbooks, students are exposed to complex and constantly changing data that can fit on a thumb drive. The implications to educators are that we need to think about the data we are using when teaching statistics and whether these data are relevant to today's students. Students today are in need of a new curriculum (Gould). There is more work needs to be done in statistics education even though much work has been done through the reform of statistics education (Easterling, 2010). The progress depends on how well we bring interesting real-life data into the classroom (Easterling; Gould; Meng, 2009). In this regard, a major change in the design of statistics instruction is needed. The recent outcry of developing statistical thinking as the primary goal of statistics education (Brown & Kass, 2009; Hoerl & Snee, 2010; Meng; Nolan & Temple Lang, 2009) further confirms the need of pedagogical change in statistics education (Gould; Meng), in particular, in introductory statistics courses (Brown & Kass; Hoerl & Snee).

Never before has the need for statistics education been greater (Gould, 2010). The demand of introductory statistics courses has steadily increased each year due to the academic quantitative requirement in undergraduate studies (Soler, 2010) as well as the need of statistical thinking in the management level of the business sectors (Brown & Kass, 2009; Finzer, Erickson, Swendson, & Litwin, 2007). The demand for statistics

education coupled with the need to rethink statistics instruction in light of new technologies, tools, and data, drove the need for the study.

Instructional Design Theory and Model Building

Merrill (2002; 2009) reviewed several instructional design theories and models and identified the principles that are essential for effective and efficient instruction. Merrill's (2002) five principles of instruction include:

- Principle 1 – Problem-centered: Learning is promoted when learners are engaged in solving real-world problems
- Principle 2 – Activation: Learning is promoted when relevant previous experience is activated
- Principle 3 – Demonstration: Learning is promoted when the instruction demonstrates what is to be learned
- Principle 4 – Application: Learning is promoted when learners are required to use their new knowledge or skill to solve problems
- Principle 5 – Integration: Learning is promoted when learners are encouraged to integrate the new knowledge or skill into their everyday life

The Pebble-in-the-Pond instructional design approach incorporates First Principles of Instruction into an instructional product emphasizing task-centered and content-first design (Merrill, 2007). The emphasis of Merrill's instruction centers on a real-world whole task and includes four phases of learning: activation of prior experience, demonstration, application, and integration into real-world activities. With a problem progression approach, the whole task that needs to be solved is first shown to the students. A series of subtasks with increasing level of complexity are then taught and

demonstrated. Students are instructed to apply previously learned topics to solve the new subtask included in the series. Repeating this same cycle of presentation, demonstration, and application, students receive less and less guidance each time a new subtask is presented. In the end, it is expected that students are able to integrate what they have learned to complete an ill-structured conventional whole task without further guidance (Merrill & Gilbert, 2008).

In an effort to align with the reform movement in statistics education, educators applied instructional models and theories such as cognitive theory (Lovett & Greenhouse, 2000), cooperative framework (Garfield & Ben-Zvi, 2009), and the constructivist theory (Roseth, Garfield & Ben-Zvi, 2008) of learning to enhance students' learning. However, the models and theories implemented into the statistical instruction have not been evaluated intensively (Richey & Klein, 2009). Although instructional design experiments have been conducted in the past for the purpose of developing learner's statistical reasoning (Cobb & McClain, 2004), they were mainly designed for students in an elementary school setting. Specifically, Merrill (2007) asks for more formal studies that implement a task-centered instructional strategy to validate its efficiency and effectiveness.

Problem Statement

Students enrolled in tertiary level introductory statistics courses lack the ability to reason and think statistically (Brown & Kass, 2009; Hoerl & Snee, 2010; Meng, 2009; Nolan & Temple Lang, 2009). Under the reform movement in statistics education, the teaching of introductory statistics focuses more on utilizing technology to foster conceptual understanding including statistical reasoning and the ability of thinking

statistically than rote procedures of merely finding a numerical solution (Garfield & Ben-Zvi, 2007; Gould, 2010). However, learners' persistent inaccurate statistical reasoning about statistical ideas has remained unchanged and is still the major issue in learning statistics (Garfield & Ben-Zvi). Guidance is needed in terms of how to design instruction for a blended learning environment that integrates technology, real data and promotes conceptual understanding.

The need for empirically assessing and validating existing and new instructional-design theories and models under various settings has been a major concern over the years (Reigeluth & Frick, 1999; Richey & Klein, 2009). Reigeluth and Frick urge researchers to apply instructional theories when designing courses to validate and improve the instructional theories. First Principles of Instruction (Merrill, 2009) have yet to be employed adequately with different disciplines. Thus, verifying instructional design in different settings with different audiences focusing on the four-phase cycle of instruction: activation-demonstration-application-integration is needed.

Dissertation Goal and Research Questions

An introductory statistics course was designed based on Merrill's First Principles of Instruction (2002). The goal was to understand how the course design based on First Principles of Instruction can facilitate tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. The 16-week course was delivered in a blended format at a two-year community college. The design integrated relevant technology and real-world data, and used a task-centered instructional strategy (Merrill, 2007). Merrill's First Principles (2002) of activation, demonstration, application, and integration were served as the overarching framework for

the cycle of instruction, while the Pebble-in-the-Pond approach (i.e., task-centered, content-first) instructional strategy (Merrill, 2007) was used to implement the principles. Using a descriptive case study design (Yin, 2009), the following research questions guided the investigation:

1. How do Merrill's First Principles of Instruction guide the development of an introductory, technology-enhanced, statistics course?
2. How can *StatCrunch*, a web-based social data analysis site, be used to support meaningful learning?
3. How does statistics instruction designed according to Merrill's First Principles improve teaching and learning quality (TALQ) and develop statistical conceptual understanding?

Relevance and Significance

Using technology for developing concepts and analyzing data when teaching introductory statistics is one of the six recommendations promoted in the GAISE project (Franklin & Garfield, 2006). However, the implementation of technology into an introductory statistics course should go beyond the basic level of utilizing, for instance, built-in functions of a graphing calculator for the sole purpose of obtaining a numerical solution. Rather, the focus should be placed on the interpretations of the data or scenario (Chance, Ben-Zvi, Garfield, & Medina, 2007).

Mason, as cited in Madge, Meek, Wellens, and Hooley (2009) and McLoughlin and Lee (2007) suggest that social software such as blogs, wikis, and social networking services (SNS's) such as *Facebook* and *MySpace* could potentially become useful tools of teaching and learning either with formal educational objectives or informal learning

(Selwyn, 2009). The rapid growth of advanced technologies has successfully changed the learners from being passive content consumers into active co-producers in the process of learning (McLoughlin & Lee). The sociability aspects of the social networking services support the learners within the same social environments to interact, collaborate and build knowledge jointly (McLoughlin & Lee; Selwyn).

StatCrunch (www.statcrunch.com) is a web-based statistical software providing a full set of statistical analysis including numerical summaries and graphical displays covered in introductory statistics courses; it is one of the social data analysis sites developed that allows users to share data sets, results, and reports in the online community. *StatCrunch* provides the sharing capabilities within the site that benefits teaching and learning. Instructors can share a large number of data sets (more than 12,000 are currently available) with their students while students can search for interesting data sets that motivate them to emulate and strengthen their skills of analyzing data (West, 2009).

In addition to the sharing of the results, the 'social' aspect of the site also allows the communication with one another within the site. Moreover, the capability of setting up user groups enables the instructors of introductory statistics courses to facilitate workshops. Student members participate in sharing their results of data analysis along with their interpretation of the data with one another and comment on each other's results and interpretation (West, 2009). It is through the discussion that stimulates students to carefully examine data in order to understand the data's context and implications. Such training induces more thoughts on statistical reasoning and critical thinking (Chick & Pierce, 2010).

Choosing Merrill's First Principles of Instruction when designing an instruction to teach blended introductory statistics at the tertiary level is appropriate. The emphasis of Merrill's instructional design is using a progression of whole tasks that are real world activities (Merrill & Gilbert, 2008). Utilizing the real world tasks in instruction agrees with GAISE recommendation of *using real data* when teaching introductory statistics courses (Franklin & Garfield, 2006). Trumpower (2010) documents that students often have difficulties identifying and interpreting the significance of the numerical results because of their lack of interest in the variables presented in the questions. Using real-world data can stimulate the interest in learning statistical principles (Chick & Pierce, 2010) as well as thinking about the meaning of the results (Trumpower).

In addition to the problem-centered instruction technique, peer interaction in the forms of peer-sharing (activation principle), peer-discussion and peer-demonstration (demonstration principle), peer-collaboration (application principle), and peer-critique (integration principle) is highly promoted in first principles of instruction (Merrill & Gilbert, 2008). Peer interaction activities encourage active learning in the (virtual) classroom. Consequently, by adequately implementing the fundamental strategies of instruction, effective, efficient and engaging learning will occur (Merrill, 2008).

With a progression of whole tasks approach, students have the chance to self-evaluate constantly through each stage of learning. In the meantime, through constant evaluation, instructors could help students improve their learning by providing feedback along the way. The inclusion of peer-critique in the instruction further extends the assessment to include constructive recommendations from the peer that benefits the students involved in the process of peer-evaluation. The GAISE recommendation of

using assessments to improve and evaluate student learning, and *fostering active learning in the classroom* discussed previously are yet coincided with another two guidelines that are included in GAISE recommendations (Franklin & Garfield, 2006).

Merrill's First Principles of Instruction could support student's *conceptual learning rather than mere knowledge of procedures*, one of the GAISE recommendations. A task-centered instructional strategy along with the peer interaction facilitates conceptual understanding. When a whole task is presented to the students, students need to be able to analyze the scenario and identify a suitable method of statistical analysis. During the process of peer-discussion, students need to be able to explain their reasoning to fellow students about why they chose the statistical analysis to solve the whole task or problem. Selecting the correct approach and convincing others involve clear conceptual understanding. Being able to analyze and interpret data helps learners to understand the world. Implementing Merrill's First Principles of Instruction into the design of a tertiary level introductory statistics course has the potential to achieve the imperative and ultimate goal of statistics education to "prepare citizenry for thinking and computing with data" (Gould, 2010, p. 298).

As a result, the relevance and significance of the study are threefold. First, one of the recommendations in GAISE is to use real data when teaching introductory statistics courses. As a result of technology in this modern world, learners are exposed to and surrounded by data on a daily basis. Bringing the practical, real-world data produced in the social life such as *Facebook* into the classroom of introductory statistics courses encourages instructors to go beyond the flat structures of using well-formulated examples provided in the texts, but rather, design instruction with authentic data exploration

experience for the learners. Second, how social networking tools can be used in blended learning environments to support the teaching has not yet been documented adequately (Arnold & Paulus, 2010). Specifically, analyzing data generated from *Facebook* through the social data analysis site *StatCrunch* integrates the practice of technology as well as real-world social life into introductory statistics curriculum. This integration can provide the instructors teaching blended tertiary level of introductory statistics courses to experience a new level of pedagogical strategy. Finally, although emphasizing statistical literacy and developing statistical thinking is the first recommendation suggested in GAISE guideline, it is the most challenging (Brown & Kass, 2009; Garfield & Ben-Zvi, 2007; Hoerl & Snee, 2010). With the implementation of Merrill's First Principles of Instruction in designing the introductory statistics courses, the impact on students learning introductory statistics could be documented. The outcomes can be valuable and can serve as experiences for the current and future instructors teaching blended tertiary level statistics courses. Consequently, there is a need to document the effectiveness and the efficiency of implementing First Principles of Instruction when designing the blended introductory statistics course at a tertiary level and understand the impacts of First Principles of Instruction have on improving student's statistical thinking.

Limitations and Delimitations

Limitations

Although beyond researcher's control, some factors may have impacts on the study results. The limitations of the study include:

- Although the results of the study can be generalized to the theoretical propositions through replication, they cannot be used for statistical generalization. That is, the

findings of the study should not be generalized to all the other tertiary level introductory statistics courses since the case in the case study does not represent a sample (Yin, 2009; 2012).

- Since there was no replication involved in the study, the results of the study can only be applied to the participants of the case study.
- Due to its descriptive case study design, causality cannot be established in the study (Yin, 2009). That is, even the results of the study show students' capability of thinking statistically, it cannot be concluded that the implementation of Merrill's First Principles of Instruction into introductory statistics courses causes the improvement.

Delimitations

The case study was conducted by purposefully imposing the following constrains to confine its scope of the research.

- Participants were restricted to those students who enrolled into a hybrid online statistics course at a two-year community college in Greater Los Angeles area.
- The following topics were covered in the introductory statistics course for the study: descriptive statistics, probability, probability models, sampling distribution, inferences, and two-sample inferences.
- Three instructional instances for each topic were designed according to Merrill's First Principles of Instruction and delivered as teaching examples and homework assignments.
- The research study was restricted for the duration of one semester (16 weeks).

Definition of Terms

To clarify the understanding of the terms used throughout the study, the following definitions are provided.

First Principles of Instruction: An instructional theory incorporating five principles that are essential for effective and efficient instruction. The five principles of instruction are problem-centered, activation, demonstration, application, and integration (Merrill, 2002; 2009).

Pebble-in-the-pond instructional design: A problem progression approach that integrates First Principles of Instruction into an instructional product emphasizing task-centered and content-first design (Merrill, 2007). With less and less guidance throughout the instruction, learners are expected to be able to integrate what they have learned to complete an ill-structured conventional whole task without further guidance (Merrill & Gilbert, 2008).

Statistical literacy: Basic statistic skills include data consciousness, an understanding of statistical concepts and terminology, knowledge of data collection and generating descriptive statistics, interpreting the results using non-technical terms, and communicating the results with people who are not familiar with statistics (Rumsey, 2002).

Statistical reasoning: Understanding statistical processes and being able to interpret statistical results (Garfield, 2002).

Statistical thinking: Being able to view the entire statistical process as a whole and asks "why" to question and investigate the issues through the context of a problem (Chance, 2002).

Summary

Chapter one introduced First Principles of Instruction, the instructional design theory, as the building frame of an innovative pedagogical design in an attempt to remove the obstacles that statistics education is currently facing. The goal was to understand how this innovative pedagogical design based on First Principles of Instruction can facilitate tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. Three research questions that guided the investigation were presented. The relevance and significance derived from the need to document real-world data exploration experience for the learners, social networking sites to support the teaching, and the impacts of First Principles of Instruction on learners' ability to think statistically were detailed. Finally, limitations and delimitations were summarized, and terms relevant to the study were defined.

Chapter 2

Review of the Literature

Introduction

Chapter two presents a review of the literature in real data utilized in statistics courses, technological tools implemented in statistics courses, social networking services implemented in teaching, instructional theories employed in statistics course design, and Merrill's First Principles of Instruction supported in course design.

Real Data Utilized in Statistics Courses

Much research on implementing real-world data in teaching introductory statistics is available. Ridgway and Nicholson (2010) urged the educators to provide tasks that are relevant to students when teaching statistics. A group of ninety students aged 13-15 from four different schools was evaluated about their statistical literacy using mashup presentations that comprised interactive multivariate displays of survey data together with newspaper articles related to the topic of the interactive displays. Students were asked to create open responses such as writing a letter to the editor or creating a video or PowerPoint in response to the display. Even though untaught with formal statistical ideas, a majority of student work was well presented in terms of style, sense of audience, or structure and logical coherence. The results were contrary to the majority of research results supporting the idea that students have difficulty comprehending basic statistical ideas when learning statistics. The researchers speculated that students' difficulty with comprehending statistical ideas could be a result of depriving of the use of real, authentic

data. When isolated tasks that are devoid of context are presented to the students, the irrelevant technical work becomes meaningless to the students. On the other hand, tasks that are relevant to students can increase student engagement, and thus, students are more capable of demonstrating what they understand.

Gordon and Finch (2010) demonstrated how using real-world data could improve learners' critical thinking. In 2008, with a purpose of training first year undergraduate students to critically utilize and evaluate statistical information, staff in the Statistical Consulting Centre (SCC) at the University of Melbourne developed the course *Critical Thinking with Data* (CTWD). Since the course was designed to provide fundamental ideas about statistical literacy, the math component was removed from the design of the course. Students taking CTWD were asked to respond to questions (orally and in writing) regarding research and arguments based on data. Using a topic-based approach, the CTWD course included a total of 15 topics categorized in four themes (finding data as evidence; examining evidence in data; understanding uncertainty in data; and drawing conclusions from evidence in data). Three researchers with strong statistical backgrounds and from different disciplines were invited to give lectures on an application in their area. Media reports with rich representation such as video clips and images that gained popularity among students were included as examples to motivate students' learning. With a dramatically different approach of teaching/learning statistics, student feedback exposed students' concern of not knowing what was expected from them, especially the assessment. However, the majority of students agreed that, after taking the course, they "felt confident about critically evaluating media reports of quantitative data" (78%), and they "had developed their capacity to think about quantitative information" (81%). This

approach, however, is not achieved without difficulties. Finding instructors who possess the right skills and experience, and who are willing to teach the course with a non-mathematical approach has become a major challenge for the course developers. In addition, finding rich media content for examples and assessments is nonetheless an ongoing and time-consuming task.

In line with the importance of using real-world data, research has demonstrated the usage of archived databases when teaching statistics (Lee, 2010; Meier, McCaa, & Lam, 2010). According to Lee, real data collection is time consuming, especially with a large set of data. However, the experience of going through the process of data production is valuable and should not be ignored in the process of learning statistics. The cleaned and artificial data provided in most of the statistics textbooks deprive students' opportunities in experiencing data exploration. Lee recommended using the online database developed by Lee and Famoye (cited in Lee) where data collected through ongoing hands-on activities were stored. The data cumulated in the database inherit the nature of real-world data of being real, messy, and large. To help students learn to diagnose the potential issues in the process of data production, Lee addressed the issues and demonstrated with the selected-real-time hands-on activities stored in the database. The major data production issues addressed were (1) choice of measurement units, (2) robustness of measuring techniques, (3) the operational definition of variable, (4) subjective sampling or random sampling, (5) outliers vs. errors, (6) observational vs. experimental study, and (7) underline target population.

With the world's largest repository of census microdata, Meier et al. (2010) described the pros and cons of the use of Integrated Public Use Micro Series (IPUMS) in

their introductory statistics taught in two universities in the U.S. IPUMS is the largest repository of census microdata in the world containing individual responses to census questionnaires conducted in more than 84 countries (representing more than four-fifths of the world's population) from 1960 to the present. Although census microdata have been made available as a teaching tool through the IPUMS-International project, the data accessibility could still be challenging. Another challenge of using the microdata is the compatibility of the samples created over time in different countries due to the lack of coordination among different national statistical agencies. Nonetheless, Meier et al. claimed that using IPUMS data in teaching statistics facilitated students' learning through real-world data to answer important questions. In addition, due to the nature of the data being collected across time from countries worldwide, students gained insight about other countries and developed general global awareness.

In addition to seeking real-world data to incorporate into the teaching of statistics, research has shown different approaches of implementing real data. One approach is to ask students to collect their own data (Libman, 2010) and the other approach is to gather data generated by students enrolled in the class (Neumann, Neumann, & Hood, 2010; Zeleke & Lee, 2010). Based on a constructivist approach, Libman (2010) integrated real-life data collection as an alternative teaching strategy to motivate students taking the control of learning in an introductory statistics course at a teachers college. Students were informed in the beginning of the semester that they were required to collect data based on their topics of interest and conduct descriptive statistics analysis. Descriptive statistics, in general, include topics of graphical display, numerical analysis, and association between two variables. Students were requested to formulate specific questions they wished to

explore from their own data collection based on the statistical tools they had learned from each topic. The researcher reported that due to its relevance to individual student's personal or professional life, the data collected by the students generated meaningful and countless discussions between students and instructors. Students showed great enthusiasm to deal with data. Many students went beyond the assignment requirement to explore their outcomes. Homework assignments were no longer static but full of challenge, which reflects the true nature of the real-life data analysis. With such a teaching approach, students became "knowledge producers rather than knowledge consumers" (p. 14). From student feedback, students reported that they were "using their minds" when learning the topics and not just "for the exam." Many students also reported that they believed they have learned something useful that they could use for the future in their lives. Although without formal empirical validation, the average grade of the students showed an increase of more than 0.5 standard deviations higher than the previous classes.

Neumann et al. (2010) conducted a mixed method study in a university introductory statistics course to understand how the usage of student data gathered from the students enrolled in the course affects student engagement in learning. A 17-question survey including quantitative and qualitative questions was given to approximately 225 behavioral and social science majors in the beginning of the course. Subsequently, data collected from the survey were used as real-world data to connect students in learning various statistical topics discussed throughout the entire course. An interview was conducted in the semester following the course completion. A random sample of 38 students, stratified according to their final grades, participated in the interview and

replied to the semi-structured open-ended question “What are your thoughts on the use of the data gathering survey in the course?” In addition, six questions required a rating, and questions regarding student demographic information were also gathered to investigate the effectiveness of the usage of student data in teaching statistics. Results showed that students surveyed agreed that studying student data created interest in learning statistics, increased the relevance of studying statistics, and helped them understand statistical concepts. Moreover, students also agreed that studying student data reduced their anxiety and increased their motivation in learning statistics.

Incorporating in-class activities generating real data from students in a calculus based introductory statistics course taught primary to science majors and online activities developed by Lee and Famoye (as cited in Zeleke & Lee, 2010), Zeleke and Lee developed lesson plans to enhance conceptual understanding. Four components were included in each activity: data generation, descriptive data analysis, relating information from data to statistical model, and making conclusions. Prior to data collection, students discussed and reached a consensus of data measurement (how to measure hand size, for instance). After collecting their own data, students worked in groups to make sense of the adopted statistical process for data analysis. Students made conclusions by comparing results of their own data with the results from across the nation by accessing to the online real-time database developed by Lee and Famoye. The survey conducted at the end of the semester showed that more hands-on activities with data generated from students are preferred from the students’ perspective.

DePaolo and Robinson (2011) reported a study where real-life data employed in the introductory business statistics course were generated from an on-campus café shop run

by a group of business students from the same college of business. When a submarine sandwich shop on campus closed the business, undergraduate business students at a midwestern public university devised an innovative plan to launch a student-run café to serve clientele in their college of business. This student-run business provided business students opportunities to apply what they had learned in the classroom about setting up a business in a real-world phenomenon. In addition, time series data were collected for students taking the business introductory statistics course to analyze and tie the statistical results to a business context to deduce strategies and make suggestions to the manager. Data were collected over 48 days in the spring semester of 2010 from three sources: total daily sales in dollars, the number of items sold daily for each food item (including soft drinks, sandwiches, and cookies), and maximum daily temperature. The staff at the café believed that weather played a role affecting the sales. They believed that when the weather was cold, people tended not to leave the building and therefore ate at the café. On the other hand, the sales dropped due to more outdoor activities during the warm days. The researchers presented examples of how the café data can be used to demonstrate some basic statistical concepts through time series and forecasting analyses.

An innovative teaching plan of learning through real data is also documented in the literature. That is, student teachers learned how to design activities for teaching statistics based on real data. Chick and Pierce (2010) reported an effective and practical approach to assist student teachers to produce content-related lesson plans with real data. In the first year of the experiment with a cohort of 27 pre-service elementary teachers enrolled in the course, student teachers were supplied with a statistically rich and regularly updated website of a local water company in Melbourne, Australia to identify topics that

could be taught using the water storage data. Working in pairs, 13 lesson plans with an objective of teaching statistics were developed. The results showed that the teachers failed to see the teaching opportunities and underutilized the real-world data when forming teaching plans. In nearly half of the proposed teaching plans, student teachers could not connect the teaching instructions with the original water storage data. Having learned the lesson from the previous year, the researchers provided an intervention with a framework of planning questions using the latest results in 2008 Olympic Games to help the new cohort of another 27 pre-service elementary teachers to identify mathematical teaching plans prior to the creation of statistical lesson plans with water storage data. In this workshop of promoting ideas to produce lesson plans, the workshop leader provided her perspectives of learning opportunities from the latest Olympic results. Student teachers also discussed and exchanged ideas. With the experience of identifying and implementing learning opportunities obtained from the workshop, 14 lesson plans using water storage data and developed by the new cohort showed that the intervention helped the student teachers to produce more appropriate and content-related statistical lesson plans with the real-world water storage data.

Technological Tools Implemented in Statistics Courses

One of the GAISE recommendations is to use technology for developing conceptual understanding and analyzing data. Many researchers have reported on how and what technologies have been implemented into the design of introductory statistics courses in response to this recommendation. The use of technology reduces the computational time so that the instructors can spend more time on teaching conceptual understanding. Using a graphing calculator is perhaps one of the most commonly applied technologies in a

class setting due to its handiness. Tan (2012) conducted an experimental study to examine if there was significant impact of using graphing calculator as an instructional approach when teaching topics of probability distribution (including random variable, Poisson distribution, binomial distribution, and normal distribution) at a private university in Malaysia. Pre-university students (N = 65) were assigned to either an experimental group (using a graphing calculator instructional approach) or a control group (using a conventional instructional approach). Students in each group were classified as low, average, or high achievers based on their math final exam scores from the previous semester. A Probability Achievement Test (PAT) was given to all the participants in both experimental group and control group at the beginning and at the end of the semester to measure their performance. To ensure consistency, the same instructor with the only exception of different instructional approach taught both groups. Prior to the beginning of the study, an independent t-test on the mean math final exam scores from the previous semester revealed insignificant difference between experimental (mean = 73.12, SD = 19.874) and control groups (mean = 73.06, SD = 19.733). The results of the pre-test confirmed further that no significant difference found between experimental (mean = 1.99, SD = 1.954) and control groups (mean = 2.95, SD = 2.630) with respect to their math competency prior to the learning of probability. However, post-test results showed statistically significant higher achievement in experimental group (mean = 75.71, SD = 5.037) than that in the control group (mean = 42.19, SD = 23.162). The most remarkable result was that the implementation of the graphing calculators when teaching probability significantly improved the performance for all the levels of participants before the study in the experimental group (mean = 77.94, SD = 1.589 for high achievers;

mean = 75.45, SD = 5.395 for average achievers; mean = 71.64, SD = 6.785 for low achievers) whereas no satisfactory learning results were observed in the control group regardless of the levels before the study (mean = 57.48, SD = 13.358 for high achievers; mean = 31.29, SD = 24.921 for average achievers; mean = 22.80, SD = 14.933 for low achievers). In addition to the quantitative results, the researcher also analyzed the qualitative data through the collection of the journal entries from the participants. Students' comments made in their journals showed that participants in the group where graphing calculators were employed interacted with each other more and were enthusiastic in exploring different methods to solve the problems due to the reduction of calculation time through the usage of the graphing calculators. In contrast, comments made from students in the control group showed a negative view of learning probability as boring. The long process of calculation through the formulas created a passive learning experience with little interaction among the peers. Tan concluded that the implementation of the graphing calculators when teaching the topics of probability distribution enhanced the learning of students at all levels (high, average, and low). It was especially beneficial to those students who were the average and low-level of achievers. The shortening of the process of tedious calculation created a student-centered learning environment where students could actively interact and discuss questions related to the concept.

Due to the importance of students' capability of making decisions using statistical results, Shaltayev, Hodges, and Hasbrouck (2010) stressed that there was a need to find an easy-to-learn software program to handle the computational procedure of the statistical analysis. Shaltayev et al. claimed that using a learner-friendly software tool reduced the learning curve during the time of teaching. In the meantime, teaching time can be more

effectively used in exploring conceptual understanding instead of spending a substantial part of the lecture learning the software tool operation. In order to test if the Excel-based statistical analysis software package VISA (Visual Statistical Analysis) was an intuitive enough tool, Shaltayev et al. conducted an empirical experiment in spring 2006. In the experiment, one instructor using the same lecturing materials taught three sections of a business statistics course. Two of the three sections of the course were taught in a computer lab whereas the third section was taught in a regular classroom equipped with a podium computer and a projector. Students participated in the sections where the lectures were conducted in the lab had a hands-on opportunity to learn the tool while students in the regular classroom section learned the software tool through instructor demonstration only. Student grades based on quizzes, homework assignments, tests and a final exam were used to compare student performance between the two methods. Additionally, teaching effectiveness was evaluated using the IDEA (Individual Development and Educational Assessment) student rating system. Results from student grades and IDEA ratings showed that regardless of the delivery method of the software package (teaching by providing hands-on opportunities or through demonstration only), both the grades and the evaluation ratings appeared to be the same between the two teaching methods. Based on these results, Shaltayev et al. concluded that VISA was an easy-to-learn software package and there should be no limitations imposed on student learning. Shaltayev et al. described that the usage of VISA package required very little computer skills except some basic Excel commends such as copy and paste. Using the VISA package to analyze statistical data involved answering a series of questions related to the data collected and the objective of the problem to be addressed. Once these questions were correctly

answered, an appropriate statistical test from the VISA package could be selected. The process of using the VISA package for statistical analysis eliminated the need to memorize tedious and complicated formulas.

In addition to statistical software packages and graphing calculators, another commonly used technology taught in tertiary introductory statistics courses to facilitate conceptual understanding of abstract ideas is the computer simulation. Through the usage of simulation, abstract concepts such as sampling distributions, regression analysis, and probability become less challenging. Mills (2005) conducted a randomized experiment on the concepts related to the Central Limit Theorem (CLT) through a volunteer group of undergraduate students taking introductory statistics course in a research university. Students were randomly divided into two groups: traditional group (control group) and Computer Simulation Methods (CSM) group (treatment group). No statistically significant difference was found between the two groups on their pre-test results; however, the post-test results of the CSM group showed a statistically significant higher achievement than the post-test results of the traditional group ($t = 2.35$, $p = 0.026$). Statistically significant results were also found between pre-test and post-test within the CSM group ($t = 4.3$, $p = 0.001$). These test results indicate the effectiveness of the computer simulation in enhancing students' conceptual learning. In addition, the attitude survey shows that students in the CSM group have more positive attitudes toward their instructional unit than their counterparts of students in the traditional group. However, the follow-up test used to evaluate student's conceptual understanding on CLT over a longer period of time shows no statistically significant difference between the CSM and the traditional groups ($F = 1.01$, $p = 3.23$). Mills argues that the formulation of concept on a

specific topic requires the integration of other related topics and needs a longer period of time to become mature. The insignificant results may be due to the limited time between the pre- and post-tests as it takes time to complete the ideas transformation.

Using wikis to promote learning (Ben-Zvi, 2007) is innovative in the field of statistics education. Ben-Zvi contends that active learning, as suggested in the GAISE guidelines, can be best achieved through collaboration. Therefore, the collaborative activities employed through the wikis are suitable to achieve the suggested active learning. To be in line with the call of statistics reform of emphasizing the learning of statistics on statistical literacy, reasoning, and thinking, Ben-Zvi proposes the following activities designed in the wiki environment: interpretations and critique of articles and graphs; generating a glossary of statistical terms in collaboration for assessing student statistical literacy; collaborative short essay writing and solving open-ended statistical problems collaboratively for assessing student statistical reasoning; and collaborative statistical projects for assessing student statistical thinking. In addition, student personal diaries can also be designed into a wiki-based environment to help the instructor understand student's learning progress. In the meantime, instructors can use that information obtained from the diary to modify the instruction.

The use of clickers has becoming more popular recently in the educational setting. Two studies examined the clicker use when teaching introductory statistics. One examined the use of clickers employed in a large class format (Kaplan, 2011) and the other examined how the use of clickers might affect student engagement and learning (McGowan & Gunderson, 2010). Confronting the challenge of fostering active learning with large class format, Kaplan employed the usage of Personal Response Systems

(clickers) in her introductory statistics course to facilitate better student-teacher interactions. Twelve activities were developed to enhance students' conceptual understanding of various topics including sampling, variability, probability models, sampling distributions, confidence intervals and hypothesis testing. Using large data sets generated from the large numbers of students (120 students in each lecture), responses gathered from students' clickers became a learning asset to assist the conceptual understanding of statistical inference. Two activities were described in this case study report to illustrate how clickers were used to engage student's learning. The Gettysburg Address activity was designed to address the conceptual understanding of sampling bias and variability that may occur from samples selected through non-random sampling methods. Students were asked to estimate the mean word length of the Gettysburg Address from samples selected using 1) self-determined selection, and 2) technology generated random number list. The results of students' respective estimated mean word lengths were collected via clickers. Charts displayed that although some individual students could estimate the mean word length quite well through self-selected samples, the variation of the word lengths collected from non-random self-selected samples for the entire class was much higher than the variation of the word lengths collected through random samples from the entire class. Although not covered at the time of this activity, students were asked to calculate the mean of all the means collected from random samples. Thus, the concept of sampling distribution was informally introduced. Another activity involved cell phone usage while driving. The Cell Phone Drivers activity was based on a scenario that a legislator claimed that the cell phone usage while driving was reduced to less than 12%. However, while waiting for a bus, a student noticed that 4 out

of 10 people drove by were using their cell phones. In this activity, students were first asked to discuss the qualification of conducting a hypothesis test and realized that the sampling distribution was skewed due to the smaller sample size of 10 drivers. Thus, the hypothesis test could not be conducted under this situation. Students agreed to increase the sample size to 100. Through simulation, a new set of 100 random numbers was generated to represent the 100 drivers. Since the assumption of the population proportion was 12%, numbers 1 through 12 represented drivers talking on their cell phone while numbers 13 through 100 represented drivers not talking on their cell phone. Simulation results were entered through clickers to form a graph of sampling distribution of the sample proportions for students to examine the eligibility of conducting a hypothesis test.

McGowan and Gunderson (2010) designed an experiment to explore how the use of clickers as a pedagogical tool might affect student engagement of learning. The experiment involved students enrolled in introductory statistics courses from January to April in 2008 at a large mid-western university in the US and took place during the 90-minute lab sections taught by a team of 24 Graduate Student Instructors (GSIs). A total of 1197 student data were included for the analysis. Three aspects of student engagement were considered: behavioral engagement (following the instructions and doing the work), emotional engagement (interest, values, and emotions), and cognitive engagements (self-regulation, motivation, and effort). Student learning was measured using validated instruments including four topic scales (normal distribution, sampling distributions, confidence intervals, and significance tests) as well as the Comprehensive Assessment of Outcomes in a first Statistics course (CAOS) from the ARTIST (Assessment Resource Tools for Improving Statistical Thinking) project. The treatment of the experiment was

the “clicker use.” Three components of clicker use that might affect student engagement and learning were considered: frequency (High, Low), agglomeration (Off, On), and external incentive (High, Moderate, Low). The number of clicker questions asked during a lab session defines the frequency as high (at least six clicker questions were asked) or low (3-4 clicker questions were asked). Agglomeration refers to asking at least 3 clicker questions consecutively (Agglomeration = On) or clicker questions were dispersed throughout the session (Agglomeration = Off). External incentive was considered in terms of tracking student names and assigning grades based on participation (High), tracking student names but no grades assigned (Moderate), and neither tracking nor grades assigned (Low). The results showed little evidence that clicker use could affect student engagement regardless of the aspect of emotion, cognition, or behavior. On the other hand, however, student learning could be improved if not too many clicker questions were asked throughout the class session. Results also showed that imposing external incentive (tracking student names as well as assigning grades) encouraged students’ participation of clicker use.

Not all the technologies were found useful in enhancing statistics learning. With an objective of investigating whether the offering of videoed lectures affect students’ learning, Evans, Wang, Yeh, Anderson, Haija, McBratney-Owen, et al. (2007) compared students’ learning outcomes obtained from the course taught traditionally in Fall 2004 with the outcomes obtained from the course offering distance option that included video access available for all the students in the course taught in Spring 2005. The researchers found that the class offering recorded class lecture videos synchronized with PowerPoint lecture notes did not outperform the class with no recorded videos offered in the previous

term. In fact, the exam grades showed statistically significant lower in the class with recorded videos available than the class with no recorded videos available for the students (p-value < 0.01).

Social Networking Services Implemented in Teaching

Despite that social networking services have become popular among college students, the conservative and slowly adopted attitude toward new technology in higher education has not yet picked up the trend and fully taken the advantage to integrate it into pedagogic teaching and learning process (Roblyer, McDaniel, Webb, Herman, & Witty, 2010). Roblyer et al. studied the adoption and usage of *Facebook* between college faculty and students at a mid-sized, southern public university in the U.S. and found that *Facebook* usage for instructional purposes was the least-common use in their practice. However, perspectives on using *Facebook* for instruction-related purposes showed quite different results. While Faculty members considered the technology was not for education, students were more likely to agree that *Facebook* was a convenient tool for education.

College students' attitude toward the usage of *Facebook* in learning is not always the same, though. In the U.K., researchers studied how first-year undergraduate students at a British university utilized a university *Facebook* network for transitioning into university life (Madge et al., 2009). A total of 213 (7%) campus-based first-year undergraduate students were recruited voluntarily to participate in an online mixed method study survey conducted over a six-week period in 2008. The results showed that during the pre-registration period, students utilized *Facebook* as a means to socially integrate into university life. Twenty-three percent of the surveyed students continued the

adoption of *Facebook* for social purposes after settling into university life. For some students, however, *Facebook* became more of an informal educational network than just a *social* network. These students transitioned the usage of *Facebook* for discussing academic work on a daily basis with other students (10%) or contacting faculty (1%). Qualitative results showed that students strongly disagreed that *Facebook* be utilized as a tool for formal learning. If *Facebook* should be used academically, respondents suggested that it should be used to exchange information about academic-work related matters such as due dates of the assignments and should not be used in formal learning "involving formal assessment" (p. 148).

In the U.S., DeAndrea, Ellison, LaRose, Steinfield and Fiore (2012) evaluated how a campus-only, closed online private social networking site could support freshmen prior to their arrival on campus. With a hope of easing the transition from high school for incoming college freshman, a campus-only, closed online private social networking site, SpartanConnect, was created by the housing department at a Midwestern university to provide informational resources as well as access to other students, staff, and faculty in the summer prior to the students' arrival on campus. To measure the bridging self-efficacy and academic self-efficacy, the students completed a pre-test survey prior to their arrival on the campus in the summer and a follow-up survey during the first two weeks of the semester. The bridging self-efficacy measured the extent to which students believed that the social sites could bring together students to provide adequate academic support. The academic self-efficacy, on the other hand, measured academic achievement from students' perspectives. A total of 265 freshmen students completed both of the surveys. Results revealed that although no significant relationships were found between

the use of the social networking site and academic self-efficacy, students perceived a diverse social support network during their first-year at college.

For the sole purpose of understanding specific activities in which students engaged on social networking sites (SNS) and how those activities developed informal learning, research at various educational settings took place in different countries. In Israel, a case study including a total of 47 Facebook and 26 Twitter official accounts registered from 2008 to 2010 by Israeli higher education institutes was conducted for the purpose of understanding how the use of SNS facilitated informal learning (Forkosh-Baruch & Hershkovitz, 2012). This empirical exploratory case study examined the extent the Israeli universities and colleges and subdivisions within these institutes utilized SNS in terms of content patterns, activity patterns, and interactivity within the SNS accounts. Forkosh-Baruch and Hershkovitz analyzed the descriptive statistics of the wall messages posted on Facebook fan pages that were open to the public as well as the tweets in Twitter accounts. Using content analysis, the researchers further classified all the tweets into categories for better understanding of how these tweets could facilitate informal learning. Distinction was found between tweets posted in universities' and colleges' Twitter accounts: The largest portion (43%) of the tweets posted in universities were discussions of professional materials not originated by the institutes while the largest portion (34%) of the tweets posted in colleges were discussions related to social issues. In Facebook accounts, on the other hand, a significant difference of number of likers was found between pages where wall discussions could be initiated either by the owner only ($X = 177$) or by the likers as well ($X = 677$). These results, as suggested by Forkosh-Baruch and Hershkovitz, implied that the higher education institutes should encourage interaction and collaboration in their

SNS accounts to promote informal learning. The analysis of the results also revealed that many SNS accounts were managed as commercial sites rather than focusing on social interaction. The researchers recommended the SNS sites were operated with sharing information and discussion in mind to enhance their unique characteristics and the effectiveness. Even though the overall research findings implied that the potential of SNS as ways of sharing academic knowledge in higher education institutes had not yet been established in Israel, the researchers concluded that SNS did promote knowledge sharing for the purpose of facilitating informal learning within the community.

To assist the educators in developing a more engaging and relevant curriculum for learners, Greenhow and Robelia (2009) conducted a qualitative study to understand how a selected group of public high school students and regular MySpace users formed their identity using this social networking site (SNS). These students were from low-income families living in a large metropolitan area in the U.S. In addition, the researchers studied these students' informal learning in SNS focusing on their *technological fluency* and *digital citizenship*, two of the six important competencies expected from students of twenty-first century. Defined by the International Society for Technology in Education (ISTE) and Partnership for 21st Century Skills, "*technological fluency* is the ability to select and use technology applications and systems effectively and productively, including the capacity to troubleshoot and transfer learning to new systems as they develop. *Digital citizenship* is the ability to practice and advocate online behavior that demonstrates legal, ethical, safe, and responsible uses of information and communication technologies" (ISTE, as cited in Greenhow & Robelia, p. 125). For a better understanding of how participants developed their informal learning through MySpace, data collection

involved triangulating multiple sources of data, including interviews, think-aloud, and content analysis of students' MySpace pages. The results showed that students gained technological fluency and developed the awareness and responsibilities as digital citizens during the identity formation process. However, the insufficient understanding of the copyright issues, for instance, suggested that although students had developed the concept of digital citizenship, the understanding of the importance of digital citizenship competency had yet to be fully established. Even though informal learning did occur in SNS, Greenhow and Robelia claimed that participants did not perceive the connection between online informal learning and offline classroom formal learning. In particular, students were not fully taking social sites' advantages for academic and career networking. Based on these findings, Greenhow and Robelia suggested that new learning and teaching theories needed to be developed to accommodate and maximize the benefits learners could get from SNS.

Studies investigating how SNS encourage or prevent students from formal learning were also documented. Junco (2012) examined the relationship between Facebook use and student engagement during the Fall 2010 semester at a 4-year public university in the U.S. A survey was conducted online to all the students (5415) at the university with a response rate of 44%. The survey included a 19-item engagement scale selected from the National Survey of Student Engagement (NSSE) instrument for measuring academic and co-curricular engagement, demographic-related questions, questions regarding a student’s technology use, and the items measured the Facebook use such as time spent on Facebook, how often they checked Facebook, and how often they conducted various activities on Facebook. In addition to the engagement scale obtained from NSSE

instrument, time spent preparing for class and time spent in co-curricular activities were also surveyed as measurements of student engagement. Results showed that while time spent on Facebook was negatively related to engagement, it was positively related to time spent engaging in co-curricular activities. Even though time spent on Facebook, in general, showed negatively related to engagement, a closer look at different activities involved in Facebook showed that communicative activities such as commenting on content and creating or RSVP'ing to events were positively predictive of both engagement scale score and time spent on participating co-curricular activities. On the other hand, the non-communicative activities such as playing games and checking up on friends were negatively related to engagement as well as time engaging co-curricular activities. Finally, a negative relationship existed between the frequency of Facebook chat and time spent preparing for class. Due to some positive relationship between Facebook use and student engagement in real-world activities, Junco concluded the study by suggesting the administrators and faculty adopt the use of Facebook when developing educational practices that maximize students' engagement to improve their academic outcomes.

Through empirical studies, Wodzicki, Scwammlein, and Moskaliuk (2012) examined how young adults between 19 and 29 years use the German equivalent of Facebook social networking site, StudiVZ, for informal learning and information exchange to support their educational learning. Study 1 took place during the four weeks between October and November 2008. A total of 774 StudiVZ users completed the online survey. Study 2 was a follow-up, which included 140 university students who participated in Study 1. In Study 3, the wall postings of a randomly selected group of

StudiVZ users were analyzed. Results obtained from all three studies were consistent and confirmed that young adults use StudiVZ mainly for social interaction with about one-fifth of the users involved in course-related knowledge exchange. In particular, freshmen are more frequent users utilized StudiVZ as a platform to exchange information related to course materials. According to the researchers, this result could be due to freshman not knowing anyone at the university in the beginning of their college years.

Dabbagh and Kitsantas (2012) described a learner-centered pedagogical framework to assist college instructors to demonstrate to students how to use social media to create Personal Learning Environments (PLE) that foster self-regulated learning. Dabbagh and Kitsantas strongly advocated that social media based PLEs can facilitate both formal and informal learning. However, to create and manage a PLE that can provide the learning experience the learner desires needs some training. The learner needs to effectively apply their self-regulatory skills in order to create a sustaining PLE to incorporate his or her formal and informal learning needs. According to Dabbagh and Kitsantas, the framework that assists the learners to create their customized social media based PLEs includes three levels of interactivity that social media tools provide: (1) personal information management, (2) social interaction and collaboration, and (3) information aggregation and management (p. 6). At level 1, the instructors should encourage individual learner to set up a goal of learning and create a private learning space through social media tools such as blogs or wikis using self-generating content. At level 2 of the framework, learners are encouraged to extend their private learning space to a social learning space by including some basic sharing and collaborative activities to foster informal learning. Through self-monitoring, learners are prompted to seek more formal learning tasks.

Learners at level 3 are encouraged to synthesize information gathered from the previous two levels to evaluate their overall learning experience.

Instructional Theories Supported in Teaching

Instructional Theories Employed in Statistics Course Design

To be in line with the reform of statistics education, the emphasis of teaching statistics should be placed on promoting students' development of statistical reasoning and thinking (Ben-Zvi, 2007). To achieve this goal, students should be encouraged to induce deep thinking of the materials learned. However, deep thinking cannot be developed in a traditional teacher-centered classroom. It can only be developed in a student-centered environment; Garfield and Ben-Zvi (2009) called this Statistical Reasoning Learning Environment (SRLE). The SRLE model is developed based on the constructivist theory of learning as well as Cobb and McClain's (as cited in Garfield & Ben-Zvi) six principles of instructional design. Along the line, Lovett and Greenhouse (2000) promote cognitive theory-based five principles of learning. Although these five principles of learning describe students' learning conditions while the SRLE emphasizes on the design of the learning environment, they are both designed to enhance students' statistical reasoning, critical thinking, and conceptual understanding; moreover, the information learned can be retained and transferred to the subsequent class or be applied to the real world (Garfield & Ben-Zvi; Lovett & Greenhouse).

On the other hand, the theory of collaborative learning is also highly regarded as an effective method in promoting students' conceptual understanding of the introductory statistics courses (Roseth, Garfield, & Ben-Zvi, 2008; Sisto, 2009). Students can develop their communication skills and practice how to involve in teamwork effectively as the

added benefits through collaboration (Roseth et al.). While collaboration among students in statistics classroom enhances effective learning, collaboration among statistics educators can, among other things, provide guidance to new teacher by sharing experiences (Roseth et al.). By doing so, it sustains students' effective learning in statistics without the need to sacrifice due to the new instructor's inexperience in teaching the course. Roseth et al. urge more research studies on the use of collaborative teaching in statistics to evaluate its sustainability.

Sisto (2009) employed collaborative learning theory in a tertiary introductory statistics where students with multi-nationalities learned to effectively communicate statistical results and consumed statistical information through the usage of collaborative group projects. The group project consists of three components: a business memo (interpret the findings to a non-statistician), an appendix (summarize the results to a statistician), and a PowerPoint presentation (present the process of the project development, findings as well as the reflections). In addition to the assignment, students were also involved in assessing their own project (self-assessment) and the project completed by other groups (peer assessment). Through the collaborative group projects, students not only learned statistics but also learned how to conduct self-assessment and peer-assessment, and how to write constructive and specific comments.

Based on experiential learning theory approach, Hiedemann and Jones (2010) compared the learning outcomes between students participating in academic service learning (ASL) projects and those who participated in case studies (CS). Specifically, the goal of the study was to assess students' mastery of course content through their final exams and students' perceptions of the relevance of statistics to their professional

development through a survey conducted at the beginning and the end of the academic terms. The study spanned across three academic quarters in 2008 where ASL projects were mandated for students to accomplish in four of the six sections of an introductory business statistics course and CS activities were required for the remaining two sections. The CS assignments provided scenarios in which student was acted as a statistical consultant to make a recommendation to a client through available statistical data and analyses. The ASL project involved actually working with a local farmers market organization to determine if there was a difference between the prices at the farmers market and the prices of produce sold at the local grocery stores and co-ops. Both ASL and CS emphasized real-world applications and interpreting results in layman's terms. However, Hiedemann and Jones argued that even though both ASL and CS are built upon experiential learning models, there are major differences between the two pedagogical methods. First, while the background of a CS is often unreal or historical, the background of an ASL is real and current which motivates students with more vivid and engaging experience. Second, ASL involves direct interaction with people or organizations outside the classroom, which promotes professional accountability toward the individuals or the organizations with whom they work. The result is a timely project with better quality. Finally, ASL projects provide opportunities to serve a broader community. Through the community service experience, students may view statistics as more relevant to their professional development and, thus, are more motivated to learn. Results indicated that although the mean final exam score in the ASL section (79.60) was higher than that in the CS section (77.02), no statsitically significant result was obtained for the two groups. Therefore, the study results did not provide evidence that ASL improved mastery of

course content comparing with CS. On the other hand, there was a statistically significant difference between ASL and CS groups with respect to their perceptions of the relevance of statistics to their professional development. Students' focus group responses verified the positive attitudes toward statistics resulting from the participation in an ASL project. Through focus groups conducted after the completion of the course, ASL participants evaluated the ASL project as being helpful in course content learning with respect to data collection, the inclusion or the exclusion of relevant or irrelevant data information, as well as the communication skills necessary when communicating using non-technical terms.

Widely used in the field of healthcare professions (Rogal & Snider, 2008; Vittrup & Davey, 2010), problem-based instructional approaches are extended from experiential-based instructional approaches (Savery, 2009). Based on a constructivism learning theory framework called 4MAT system, the faculty at the Cleveland Clinic Learner College of Medicine (CCLCM) of Case Western Reserve University developed a problem-based biostatistics course (Nowacki, 2011). The purpose of the redesign was to intrigue student's interest in learning statistics through connecting the role of statistics to medical research. The 4MAT system involves a learning process that engages students by answering four questions: Why? (The motivation for learning), What? (Identifying and seeking knowledge), How? (Trying out and applying knowledge), and If? (Reflecting what have learned and extending it to new setting). The Attitudes Toward Statistics (ATS) post-course survey results showed a statistically significant increase toward students' perception of the usefulness of statistics comparing with the pre-course survey results. Students reflected the new design of the course as lively and effective due to its

student-centered approach, tremendous amount of student engagement, and its emphasis on application. Nowacki contributed the students' optimism to the problem-based design that required students' active involvement in preparation prior to the class as well as discussion throughout the learning process.

Similar to problem-based learning approach, Lesser and Kephart (2011) described a case study of the design and implementation of a single lesson plan used on the first day of class in a graduate-level statistics course for K-12 teachers in the spring 2009 semester. The instructional design of the intervention involved several phases: Initial individual reflection, small group discussion, whole class discussion, and further individual reflection. Several important aspects of problem-based inquiry learning approach from this case study were highlighted: 1) While small group interactions provide students a low-stress environment to develop understandings through exchanging their reasoning with the peers in the group, whole-class discussion offers an opportunity for instructor to verify students' correct understanding and allow the learning community to build on a common conceptual ground. 2) Problems designed based on open-ended questions allow students to challenge misconceptions and wonder about implications. 3) In an inquiry-based instruction environment, both students and instructors are equally responsible for classroom conversation and knowledge construction. The instructor's role is both a facilitator and co-learner. Lesser and Kephart concluded that through the inquiry-based learning approach, students could develop quality thinking and thus, gain conceptual understanding.

Dhand and Thomson (2009) described a scenario-based approach of teaching biostatistics to veterinary students at the University of Sydney. The focus was on the real-

life problems. Four case studies were designed to teach the topics of hypothesis tests including one-sample t-test, two-sample t-test with pooled variance, two-sample t-test with unequal variances, and paired t-test. The approach used for teaching the test of hypothesis involved the following eight steps: 1) Set the context through the scenario, 2) Inform the objective of the study, 3) Descriptive analyses: Interpretation of the summary statistics and the graphical summaries, particularly the boxplots, 4) Hypothesis specification: Specify the null and the alternate hypotheses, 5) Examine the assumptions of the significance test, 6) Conduct the actual hypothesis test, 7) Make decisions by interpreting the p-value and the confidence interval and relating the test results back to the scenario in context, and 8) Implication: Other examples of similar use of the tests conducted in journal articles were presented to the students and asked for interpretation of the test results. An informal questionnaire was administered to a conveniently selected group of 24 students at the end of the semester to obtain information about students learning experience with this scenario-based approach and their perceptions about the course. About 80% of the respondents agreed that the scenario-based pedagogical approach was easy to follow and helped them to understand the concepts. However, student perceptions about the usage of learning the course remained low (42%). The author claimed, nonetheless, that the scenario-based approach was a good start in teaching statistics but more efforts were required to increase student perceptions about the applicability of the subject to their professional life.

There has been a concern about the lack of quantitative literacy in the undergraduate social science students in the UK. To address this concern, the Economic and Social Research Council (ESRC) in the UK issued several calls for proposals. In

response to the calls, Marriott & Davies (2009) designed a pedagogical instruction utilizing the evidence-based statistical problem solving approach (PSA) to teach statistics for this group of student population. In PSA, students go through a process of four stages: plan, collect, process, and discuss. To illustrate how PSA can be utilized in learning statistics, the authors provided two examples: student accommodation and crime in the neighborhood. In each example, students were actively engaged in discussing their own experiences related to the topic. Several questions emerged and led to the conduction of a questionnaire. In student accommodation, for example, questions such as what type of accommodation it was, how far the accommodation was from their classes, how much they paid in rent were included in the survey for descriptive analyses. In particular, one specific question was developed during the plan stage of PSA: Whether the average rental was the same for different types of accommodation (living at home, university-provided accommodation, or private sector accommodation). This specific question resulted in the introduction and the discussion of analysis of variance (ANOVA). Similarly, the authors suggested a typical question that can be discussed in the crime in the neighborhood activity: whether students from different universities would have different perceptions of crime in their location. Students would then learn the statistical method of chi-squared test of independence to analyze the data collected from themselves to answer this question.

Merrill's First Principles of Instruction Supported in Course Design

Literature documents the implementation of Merrill's First Principles of Instruction into course design for online courses (Francom, Bybe, Wolfersberger, & Merrill, 2009; Mendenhall, Wu, Suhaka, Mills, Gibson, & Merrill, 2006) and staff-training courses

(Collis & Margarkyan, 2005; Gardner & Jeon, 2009). When the director of the Center for International Entrepreneurship at Brigham Young University – Hawaii proposed an online course in entrepreneurship for non-business majors, the staff at university's Center for Instructional Technology and Outreach listened and implemented Merrill's task-centered instructional strategy in the course design. With the task-centered instructional strategy approach, the final exam of the course included an analysis of a new whole task. Out of the 12 students took the final exam, more than half (seven students) of the students received a grade of A or B with four students receiving a C and one student receiving a D. Students expressed overall satisfaction with the course design. The researchers concluded that the task-centered instructional strategy appears to be effective in teaching students who have no previous experience about entrepreneurship (Mendenhall et al., 2006).

For a purpose of offering more online classes with effective teaching and increasing students responsibility of learning, staff at Center for the Improvement of Teaching and Outreach (CITO), Brigham Young University - Hawaii (BYU - Hawaii) underwent a major revision of instructional strategies. Francom et al. (2009) introduced a redesign of a general education course, Biology 100, implementing Merrill's First Principles of Instruction with a task-centered approach in summer 2008 with 89 students in two classes. The redesign involved students' active participation in pre-class, in-class, and after-class activities. Prior to the class, students were assigned to read the task and the related materials in the book that would be used to solve the task. When students came to the class, the instructor first demonstrated how to solve that task using the materials students had previously read from the book, followed by a group discussion on a new

second task. The third task assigned as a homework assignment after the class was to be worked individually. Individual student posted his/her response to the third task within his/her own group to exchange ideas. All the students from the same group then collaborated on a group response and submit the completed third task to the instructor. A post-course survey showed that more than three-fourths (76%) of students enjoyed the new teaching strategy of being able to take their own learning responsibility and apply materials learned from the class to complete more relevant real-world tasks. Course instructor's confirmed this finding through informal class observations of active group discussion about the task.

In a cooperate setting, Collis and Margarkyan (2005) reported how they incorporated and extended Merrill's First Principles of Instruction into a course designed for workplace learning at Shell Exploration and Production (Shell EP). Thus, Merrill Plus was developed to reflect the specific corporate context for a business setting. In their version of Merrill Plus, six aspects were added in addition to the original five principles of instruction: Engaging in real-world problems, activating existing knowledge as a foundation for new knowledge, demonstrating new knowledge to the learner, applying new knowledge by the learner, and integrating new knowledge into learner's world. In the context of Shell EP, the six added aspects to Merrill Plus were collaboration, learning from others, supervisor support, technology support, re-use, and differentiation. Collis and Margarkyan suggested that each organization should work out on its own version of Merrill Plus by retaining the original five First Principles of Instruction and adding aspects relevant to its own practices.

Gardner and Jeon (2009), on the other hand, described the obstacles instructional designers encountered when redesigning a staff-training course employing Merrill's First Principles of Instruction to replace the original one-day face-to-face training given by the subject matter experts (SMEs) at Utah State University. The training course was to provide information on using a collegiate administrative suite Banner. Since the original training course focused solely on introducing Banner's functions rather than demonstrating and applying to real-world problems, it was found ineffective in performing complex tasks. Although the redesigned training course was found more effective than the original training course, it was not accomplished without encountering obstacles in the process of redesigning the course. The major obstacle encountered, as reported, was the difficulty that the subject matter experts (SMEs) had when producing examples of real-world tasks due to SMEs' lack of knowledge relating what a real-world task is. Another obstacle of designing the new training course was that it was time consuming when designers embedded technology solutions, such as Encoding Flash and HTML, into the design.

Although Merrill's First Principles of Instruction could be employed in the instructional design to improve the course, do they improve student learning? Frick, Chadha, Watson, and Zlatkovska (2010) designed an empirical study to answer this question. A course evaluation instrument used to measure teaching and learning quality (TALQ) was developed for students to evaluate if Merrill's First Principles of Instruction is included in the teaching of the course (Frick, Ghadha, Watson, Wang, & Green, 2009). TALQ also evaluates student's own Academic Learning Time (ALT). Traditionally, when ALT is reported to occur during the learning process, student experiences positive

learning results. The survey was administered during the fall 2007 semester at a large Mid-western university. A volunteer sample of 464 students in 12 different courses taught by eight different instructors filled out the paper form of TALQ. Instructor ratings of student mastery (level of achievement of course objectives) in the course were independently reported after the completion of the semester. The results showed that when students agreed that First Principles of Instruction were employed in class, those same students were more likely to report their positive experiences of ALT. Moreover, instructors were more likely independently rated those who reported positive experiences of ALT with high ratings of course mastery. The implication of the results, according to the researchers, is that the tasked-centered instructional strategy promotes student learning.

Summary

Chapter two included an overview of the research literature informing the instructional theory of Merrill's First Principles of Instruction supported in course design. An overview of the strategies applied in the instructional design when teaching introductory statistics at the tertiary level was also presented. The strategies include the implementation of the real-world examples, implementation of technological tools, and the incorporation of instructional theories. In addition, a review on social networking services employed in academics was provided for an overall understanding of how the usage of social networking services affect student formal and informal learning in an academic setting.

Chapter 3

Methodology

Research Methodology

With the aim of understanding how integrating technology and real data into a tertiary level statistics course affect students' statistical literacy, reasoning, and thinking, a case study research design was employed. Merrill's First Principles served as the guiding framework for the instructional design.

When the study of interest is to understand cognitive or affective aspects of learning process, the inherent limitations due to its social or behavioral nature prevent the researchers from quantitatively measuring the results. Qualitative research methods, on the other hand, could unearth subjects' thinking through open dialogues such as interviews or online postings to produce a rich description of participants' thinking (Gal & Ograjensek; Groth, 2010). Therefore, qualitative research, specifically, a descriptive case study design was employed to describe how applying First Principles can have an impact on learners' degree of thinking statistically.

Descriptive Case Study

Traditionally, the case study has not been treated as a formal research method but merely a preliminary study of some other type of research method for the sole purpose of exploring the investigation (Yin, 2009). However, Yin (2009; 2012) stressed the permissibility of using case studies to not only process but also document and analyze the implementation. Case studies emphasize the connection between a real-life phenomenon

and its context. The inclusion of contextual conditions is necessary for a thorough understanding of a phenomenon. According to Yin (2009), three conditions need to be considered for the selection of an appropriate research method: a) the type of research question posed, b) the extent of control an investigator has over actual behavioral events, and c) the degree of focus on contemporary as opposed to historical events (p. 8). Case studies ask "how" and "why" questions. Specifically, the portrayal of what happened in a particular case leads to a descriptive case study (Yin, 2012). As much as an experiment relies on the manipulation of participants' behaviors, a case study relies on multiple sources of evidence due to its lack of control of behavioral events. Case studies, unlike histories, focus on contemporary events. In this case, the goal was to understand how the implementation of Merrill's First Principles of Instruction could affect students' development of statistical thinking. In particular, the study described what happened to students' cognitive development when learning tertiary level introductory statistics. Therefore, a descriptive case study design was suitable.

In designing case studies Yin (2012) suggests these three steps: Defining a case, selecting one of four types of case study designs, and using theory in design work. Based on these three steps, the following process was adopted to answer the research questions:

1. Defining a case: The case is also called a unit of analysis. Once the case is properly defined, it is desirable to set up the time frame of the case study. This case includes the students enrolled in one section of a blended tertiary level introductory statistics course at a two-year community college in Greater Los Angeles area in Spring 2013 for duration of one semester (from February 4 to June 3, 2013).

2. Selecting one of four types of case study designs: The four types of case study designs are holistic single-case design, embedded single-case design, holistic multiple-case design, and embedded multiple-case design. According to Yin (2009), a single-case study is an appropriate design when testing a well-formulated theory. This single case is considered to be a *critical* case. Since the study was to test the impact of the well-devised First Principles of Instruction on a student's learning, an embedded single-case study design was implemented. Represented as a form of mixed methods design, embedded case design allows surveys or other research methods to be embedded within the single case study design for collecting quantitative data. While the unit of analysis was the class, the embedded subunit of analysis was the individual student in the class. The embedded survey employed teaching and learning quality (TALQ) instrument (Frick et al., 2009; 2010) for evaluating the teaching and learning quality of the designed instruction from student's perspective (Appendix A). The instrument was slightly modified to suit the study. A list of modification is illustrated below.

    - Two questions were removed from Part 1 of the survey. One question was related to participants' academic classification in terms of freshman, sophomore, junior, senior or a graduate student. The other question was about the course delivery modalities (online, hybrid, or face to face).
    - A slight change of the wording of Question 15 in Part 2 of the survey was made to reflect the specific technology used in the course. The

original question was stated as, “The media used in this course (texts, illustrations, graphics, audio, video, computers) helped me to learn instead of distracting me”. The question was modified into, “The technology used in this course (online homework, online discussion platform, *StatCrunch*) helped me to learn instead of distracting me.”

- A change of wording was made on Question 33 in Part 4 of the survey to reflect the specific coursework participants were learning. The original wording of the question was, “Assignments, tasks, or problems I did in this course are clearly relevant to my professional goals or field of work.” The modified version of the question was, “Assignments, tasks, or problems I did in this course are helping me to develop the skills of thinking statistically.”

3. Using theory in design work: It is vital to develop some theoretical propositions or theory during the case design phase. The theory development provides a blueprint for data collection. With a preliminary theory, the researcher could build and challenge this initial theoretical perspective. However, one should be cautious with this approach. On one hand, the theoretical perspective could guide the researcher in data collection. On the other hand, it could also limit the ability to discover new theories. Therefore, the researcher needs to practice with great care. Work with the initial perspective and at the same time, be prepared to modify or even abandon it after the first round of data collection. Since the study is to understand how First Principles of Instruction could affect students’

learning of introductory statistics, the initial theoretical proposition was set as the following: The impact of First Principles of Instruction on a student's learning is positive. The proposition remained unchanged throughout the entire study.

Course Design

In order to understand how the implementation of First Principles of Instruction can affect a student's learning of tertiary level introductory statistics course, instructional instances on the topics of an introductory statistics course were designed following Merrill's (2007) prescriptions for creating task-centered instruction. Materials covered in the entire course were arranged into five topics: Data Collection, Descriptive Statistics (including Regression Analysis), Probability & Probability Distributions, Sampling & Inferences on Population Means, and Sampling & Inferences on Population Proportions. To avoid the frustration of using new tools such as *StatCrunch* and *Etudes* (Easy-to-Use-Distance-Education-Software), an online discussion board, modules of trainings on *StatCrunch* and *Etudes* were included in the first week of the 16-week course along with the first course topic of Data Collection. The contents of the instructional instances for topics of Descriptive Statistics (including Regression Analysis), Sampling & Inferences on Population Means, and Sampling & Inferences on Population Proportions were derived based on Gould and Ryan's (2013) textbook and posted on weekly modules on the official course website *Etudes*. Due to time limitation, no instructional instances and projects were designed for the topics of Data Collection and Probability & Probability Distributions. The contents of these two course topics were from Sullivan's (2010) textbook. Table 1 summarizes the course design for the study.

Table 1. Course Design Summary

Topics	Materials Covered	Duration (in weeks)	Instructional Instances (Projects included)
Data Collection	Data Types, Sampling	1	No
Descriptive Statistics	Graphical display & numerical summary of a qualitative data set Graphical display & numerical summary of a quantitative data set	4	Yes*
Regression Analysis	Linear correlation & regression	1	Yes*
Probability & Probability Distributions	Probability, Probability distributions	3	No
Sampling & Inferences on Population Means	Sampling distribution of sample means Confidence interval of population mean Hypothesis testing of population mean Inferences of two means, independent and dependent samples	3	Yes
Sampling & Inferences on Population Proportions	Sampling distribution of sample proportions Confidence interval of population proportion Hypothesis testing of population proportion Inferences of two proportions, independent samples	2	Yes

*The first project included both topics of Descriptive Statistics and Regression Analysis.

Participants

Thirty-nine students were pre-enrolled into a blended tertiary level introductory statistics course taught by the researcher at a two-year community college in Greater Los Angeles area prior to the start of the semester in Spring 2013. Of the 39 pre-enrolled students, seven students failed to show up for the first class meeting and hence were dropped from the class. Eight walk-in students were added to the class on the first class meeting day. Out of the total 40 enrolled students, 30 consented to the study. Total enrollment dropped to 21 students three weeks into the semester. By the time the first project was due (the fifth week of the semester), 15 students remained in class. The semester ended with eight students actively involved in class participation including the interviews and final assessment. Two students, although officially enrolled in the class by the end of the semester, ceased participating in class discussion weeks before the end of the semester.

Those who did not consent to the study dropped the course at early stages of the study and their postings were not included for data analysis. Even though 30 students consented to the study, nine of them never participated in class discussion and were dropped prior to the fourth week of the semester. Overall, data were collected from a total of 21 students. Of these 21 participants, eight participated in the semester end open-ended interview, TALQ survey and the final CAOS assessment. Traditionally, the retention rate is relatively low in this college due to its disadvantaged socioeconomic background. Hence, this high attrition rate is typical for this online hybrid introductory statistics course.

Data Collection

Guided by the study's initial theoretical proposition, four sources of evidence were used for data collection: postings from the online discussion forum, an end-of-course comprehensive assessment, open-ended interviews, and the TALQ (teaching and learning quality) survey. An informed consent (Appendix B) was collected from the participants prior to data collection. The following describes the four types of data that were collected throughout the study.

1. **Online discussion forum data**. Postings from the online discussion forum including weekly discussions and three projects were collected and analyzed.
2. **Comprehensive assessment.** The level of mastery of course objectives (the mastery of statistical literacy, reasoning, and thinking) was assessed independently using a modified version of Comprehensive Assessment of Outcomes in a first Statistics Course (CAOS) test instrument (delMas, Garfield, Ooms, & Chance, 2007) at the end of the semester. The letter of permission to use CAOS test instrument for the study is in Appendix C.
3. **Open-ended interviews.** Eight interview questions with different scenarios of the same level of difficulty were designed for the open-ended interviews conducted at the end of the semester to eight actively participated students. An interview question was randomly selected and assigned to each participant to assess their statistical reasoning and thinking capabilities. Each interview question consisted of two parts. Students were asked to complete the first part of the interview before receiving the second part of the interview question. Appendix D shows an example of interview questions. To alleviate participants' anxiety, which may directly affect the performance, interviews

were conducted in writing using the discussion forum instead of orally. Eight discussion forums, each designed exclusively for each participant, were created for replying the interview questions. Since the scenarios were similar to what the participants had practiced regularly in weekly discussions and projects, no further explanations regarding the given scenarios and questions were provided at the time of the interviews. This procedure also helped to avoid bias. However, prior to the interviews, participants were reminded to "think aloud" when responding to the questions. Follow-up questions, such as "What do you mean by …?" were prompted whenever necessary immediately after the submission of each part of the interview questions for clarification. Specifically, students were asked to use the think-aloud method to perform the following tasks during the interview:

a. In part one, participants were asked to describe the appropriate statistical analysis process that should be employed in order to answer the statistical question given in the scenario.
b. In part two, based on the given scenario, a statistical analysis printout from *StatCrunch* was shown to the participant. The participant was asked to make a conclusion and interpretation according to the printout (Appendix D).

This think-aloud interview process enabled the researcher to capture the students' cognitive process of whether the phenomena of thinking and reasoning statistically occurred, and if they did occur, how accurate or inaccurate the process was when solving a statistical problem. Specifically, part one of the interview questions assessed student's statistical thinking capability while part two of the interview

questions assessed student's statistical reasoning capability. Statistical literacy related to basic statistical skills was assessed in the entire interview process through the students' responses.

4 **TALQ instrument.** The TALQ survey including the following student self-reported nine scales was administered at the end of the semester: academic learning time (ALT) scale, learning progress scale, learner satisfaction scale, and Merrill's five-principle scales including authentic problems scale, activation scale, demonstration scale, application scale, integration scale, and Pebble-in-the-Pond approach scale. As suggested by Frick et al. (2009), TALQ scales can serve as a baseline for course evaluation to accompany objective assessments of student learning comprehension (statistical literacy, reasoning, and thinking in this case). The results of the assessed mastery of course objectives were compared with the self-reported level of mastery of course objectives obtained from the TALQ survey. To avoid response bias, a colleague administered the survey and kept the survey results in a sealed envelope. The participants were informed prior to the survey that the access to the survey results was made unavailable to the researcher until the completion of grade submission.

Reliability and Validity

The quality of a research study can be established through the rigor of construct validity, internal validity, external validity, and reliability (Yin, 2009). Internal validity is irrelevant to descriptive studies since it seeks to establish causal relationships for explanatory studies only (Yin). Each one of the other three tests, namely, construct validity, external validity, and reliability is defined and described with respect to the study as follows.

Construct Validity

According to Kiddler and Judd (as cited in Yin, 2009), construct validity clearly identifies the operational measures that gauge the concepts being studied. Case studies risk the reputation of making subjective decisions for data collection due to the lack of properly defined operational measures. To handle this issue, Yin (2009) recommends using multiple sources of evidence including, but not limited to, documentation, archival records, interviews, direct observations, participant-observation, and physical artifacts. The essence of using multiple sources of evidence in case studies is to establish construct validity through data triangulation. The approach of applying various types of evidence in data collection is to ensure the coverage of a broader range of issues, and more importantly, to converge *lines of inquiry* (Yin). Validity can be confirmed when data have been triangulated, sources of evidence are corroborated and convergent consistently to one conclusion (Tellis, 1997).

However, the challenge of collecting multiple sources of evidence is not limited to more costly and time consuming, rather, the know-how of all the techniques required prior to data collection. Yin (2009) warns that the improper usage of data collection techniques could render a failed validity construct. Yin suggests different ways of gaining experiences of conducting case studies. One of them is to practice data collection techniques through the design of pilot studies. Another recommendation to increase the construct validity of a case study is to maintain a chain of evidence in such a way that an external observer should be able to follow the steps either from initial research questions to final conclusions or from conclusions back to initial research questions through the evidence presented in the report (Yin).

To ensure the construct validity of the study, evidence was collected through various sources including the online discussion postings, a comprehensive assessment, open-ended interviews, and the TALQ survey. Data were triangulated to form convergent lines of inquiry. The researcher maintained a chain of evidence after data collection. A pre-test study of the teaching examples and homework assignments were conducted for the purpose of refining the instructional design prior to implementation with the target population. According to Yin (2009), a pre-test study is a rehearsal prior to the formal data collection to ensure that the entire data collection plan will be carried out accordingly. In the study, real tasks were created through online social networking sites for designing task-centered teaching examples and assignments. The suitability of the real task design was tested and refined through the pre-studies conducted in two face-to-face tertiary level introductory statistics courses in the fall semester of 2012.

External Validity

External validity defines "the domain to which a study's findings can be generalized" (Kidder & Judd, as cited in Yin, 2009, p. 40). A common misunderstanding about the generalizability of case studies is that the results of a case study cannot be generalized beyond the immediate study. More often than not, the generalization refers to the statistical generalization. While statistical generalization is not possible for case studies, analytic generalization is possible for replicating the procedures in another case or cases. That is, a broader theory can be generalized through replicating using multiple-case designs (Yin, 2009). Although the current study is a single-case designed study, the external validity can be established through the replication of the study in different cases (classes).

Reliability

Reliability focuses on repeating the same case and obtaining the same results as the previous study. The goal of striving for a high level of reliability is to reduce the chances of erring and to prevent the bias in data analysis (Yin, 2009). To address the establishment of the reliability of a case study, Yin recommends that case study researchers create a formal and presentable case study database. The sources of evidence should be organized for easy retrieval by other investigators so that the written case study report would not become the sole source for reviewing the evidence. During the process, the evidence obtained from various sources should remain intact. Twisting or imposing biases on the evidence should be strictly avoided. In addition, the loss of original evidence through carelessness should be strictly prevented. To increase the reliability, a case study database was created to organize the data collected from the four data sources.

Data Analysis

Both quantitative and qualitative data were collected. Focus should not be placed on either type of data alone. Rather, one should look for the convergence of information through reviewing and analyzing data collected from different sources (Yin, 2009). Case study analysis is not easy due to its lack of fixed formulas to guide the process (Yin). Nonetheless, Yin describes four general analytic strategies (*replying on theoretical propositions*, *developing a case description*, *using both qualitative and quantitative data*, and *examining rival explanations*) and five analytic techniques (*pattern matching*, *explanation building*, *time-series analysis*, *logic models*, and *cross-case syntheses*) for analyzing case study data.

Two strategies are relevant here, namely, *using both qualitative and quantitative data* and *relying on theoretical propositions*. When quantitative data are played in a supportive role in a case study where qualitative data remain central to the entire study, the analytic strategy of using both qualitative and quantitative data becomes a powerful way to guide the analysis (Yin, 2009). The strategy of relying on theoretical propositions is to follow the hypothesized theoretical propositions set up in the beginning of the study. The proposition helps to organize the entire case study by focusing attention on the relevant data collected for the study. This strategy is especially useful with respect to the theoretical propositions originating from 'how' questions (Yin). The goal was to understand *how* First Principles of Instruction could affect students' learning of introductory statistics. Hence, it was suitable to apply the strategy of relying on theoretical propositions in analyzing the case study data.

Among the five analytic techniques, pattern matching is the most relevant in this case. The technique of pattern matching is based on matching-the-pattern logic when comparing an empirical pattern with a predicted one (Trochim, as cited in Yin, 2009). Yin claims the suitability of using pattern-matching technique in a descriptive case study with an emphasis that the predicted pattern of the studied variables should be defined prior to data collection. Based on the initial proposition that the implementation of First Principles of Instruction has positive impact on students' learning, the pattern-matching analytic technique was used to compare the predicted positive outcomes with the actual students' learning outcomes. Through the coded qualitative data as well as the quantitative data, the question of the establishment of initial proposition was answered through matching the pattern analytic technique. Theoretically, if the observed outcomes

are as predicted, a solid conclusion about the positive effects of First Principles of Instruction can be drawn. On the other hand, if the results fail to follow the entire predicted pattern, then the initial proposition is considered to be questionable. The qualitative data collected from online discussions and interviews along with the quantitative data obtained through the TALQ survey and comprehensive assessment were used to deduce a theoretical proposition that either supports or disapproves the hypothesized theoretical proposition established in the beginning of the study.

Quantitative Data Analysis

The TALQ survey included a total of 48 items. Among them, three items were related to course demographics – class rating (a 10-point Likert scale with 10 being outstanding and 1 being poor), expected grade, and self-reported course mastery (a 10-point Likert scale with 10 being high master and 1 being low master). Individual self-expected grades for the final eight participants were reported. Descriptive statistics including mean and standard deviation scores for class rating and self-reported course mastery score were calculated.

The remaining 45 TALQ survey items including 37 items of nine TALQ scales, three global rating items, and five miscellaneous items were scattered randomly throughout the instrument. A five-point Likert scale was used for each item with 5 indicating “strongly agree” and 1 indicating “strongly disagree.” The nine TALQ scales are Academic Learning Time (ALT) scale (5 items), learning scale (5 items), learner satisfaction scale (4 items), First Principles of Instruction – authentic problems scale (5 items), First Principles of Instruction – activation scale (5 items), First Principles of Instruction – demonstration scale (4 items), First Principles of Instruction – application

scale (3 items), First Principles of Instruction – integration scale (5 items), and First Principles of Instruction – Pebble-in-the-pond approach scale (1 item). Modified from Frick, Chadha, Watson, Wang, and Green (2008), the TALQ survey with items arranged by the nine TALQ scales is listed in Appendix E.

Descriptive statistics including mean and standard deviation scores for each scale of the TALQ survey were calculated. The mean and standard deviation of ratings for each scale were found based on the ratings obtained from eight participants. The individual participant's rating for each scale was first computed by finding the average of the ratings of the related survey items. For example, five items were related to Academic Learning Scale. Harry (Pseudonym is used) rated five items related to Academic Learning Scale as 4, 5, 4, 4, and 5, which gave an average of 4.4. Likewise, the average ratings of Academic Learning Scale for the other seven participants were: 4.6, 3.6, 4.4, 5.0, 4.0, 4.2, and 4.2. Using these eight ratings from the participants, the mean and standard deviation of Academic Learning Scale rating were then computed.

Nine TALQ survey items were negatively worded to ensure the internal consistency of the responses. No conflicts of item agreement/disagreement were detected. Therefore, no items were excluded from data analysis. The rating for negatively worded items was recorded reversely before averaging out with the other related survey items.

The comprehensive assessment CAOS test used to objectively assess students' mastery of the course was given at the end of the study. Summary statistics including mean and standard deviation of CAOS test scores were computed. In addition, linear correlations among nine TALQ scales, learner satisfaction scale, class rating, global rating, self-report course mastery scores and objectively assessed course mastery scores

(CAOS) were first examined through scatterplots to detect the linear pattern. The linear correlation between each pair of two variables was then quantified through the use of Pearson correlation coefficient (*r*) and reported.

Qualitative Data Analysis

Content analysis was conducted on the discussion forum postings including weekly discussions and topical projects, and the interview data for gaining an understanding of students' cognitive development of thinking statistically. Content analysis is a type of qualitative research analysis method that analyzes documents involving vast amount of textual data through comparing the similarities and contrasting the differences for a purpose of finding patterns and understanding the trends in communications (Burnard, 1996; Elo & Kyngäs, 2007; Harwood & Garry, 2003). The aim is to categorize the key issues in data (Burnard). In particular, content analysis is most useful in capturing the cognitive development in an online learning environment (Gerbic & Stacey, 2005). Elo and Kyngäs mention two types of content analysis: inductive content analysis and deductive content analysis. The inductive way is preferred when there is lack of former knowledge dealing with the phenomenon or when the knowledge is fragmented. On the other hand, the deductive approach is recommended when testing a previously developed theory in a different context. The deductive approach of content analysis is was relevant in this case since the goal was to test how the course design based on First Principles of Instruction can facilitate tertiary-level students' conceptual understanding when learning introductory statistics.

Three phases are involved in content analysis: preparation, organizing, and reporting (Elo & Kyngäs, 2007). The preparation and organizing phases are presented in

this section while reporting phase is presented in the Presentation of Results section. The preparation phase begins with the selection of the unit of analysis followed by the choice of unit of meaning (Elo & Kyngäs; Graneheim & Lundman, 2003). According to Graneheim and Lundman, the most suitable unit of analysis is the whole interview while a meaning unit can be defined as words, sentences, or paragraphs that are related to a central meaning. Four course topics, descriptive statistics, regression analysis, sampling and inferences on population means, and sampling and inferences on population proportions, were discussed in the discussion forums for the entire period of study. The unit of analysis of the online postings is the entire course topic of each individual participant. The unit of meaning is each posting posted by each individual participant. The specific steps for analyzing online postings involved in the preparation phase are as follows:

1. Since online postings were stored permanently on the online learning management system, Etudes, transcribing was not required. Transcripts of online postings were downloaded after the completion of each course topic discussion. Take the discussion topic of descriptive statistics as an example, the online postings related to the topic including weekly discussions and a topical project along with participants' critiques were downloaded and saved in one file.
2. To protect the privacy of the participants, real names were removed and pseudonyms were randomly assigned before coding.
3. Each posting within the same file was numbered according to the assigned pseudonym alphabetically for random sampling in later organizing phase.
4. Two copies of each file were prepared for the two coders for coding.

Next in the organizing phase, the content analysis process consisted of three core elements: coding the data, organizing the data, and testing for reliability and validity (Hardwood & Gary, 2003). Prior to the coding, the researcher read through the data as many times as necessary for the purpose of making sense of the data and obtaining an overall feel of the data (Burnard, 1996; Creswell, 2008; Elo & Kyngäs, 2007). When a deductive content analysis was chosen, as was in this study, a structured categorization matrix determined from literature reviews was developed prior to the coding. An example of such matrix is shown later when summarizing the organizing phase for analyzing online postings. Only aspects that fit the predetermined categorization were chosen for coding (Elo & Kyngäs; Hardwood & Gary). Content analysis is frequently criticized by its bias stemmed from the researcher's subjectivity. To overcome the judging bias, training in coding is necessary. To increase the reliability and validity of the research findings, measures of reliability should be computed and reported (Hardwood & Garry, 2003). When measuring the reliability of coding, one should start with intra-rater reliability (the coder agreeing with oneself over time), followed by inter-rater reliability (two or more coders agreeing with one another) (De Wever, Schellens, Valcke, & Keer, 2006; Hardwood & Garry). Two coders were recruited and each coder was paired with the researcher to assist with the coding. In particular, coder #1 was paired with the researcher (coder #2) in coding the weekly discussions and the topical projects of Descriptive Statistics and Regression Analysis, and the interview data. Coder #3 was paired with the researcher (coder #2) in coding the remaining two topics of Sampling & Inferences of Population Means and Sampling & inferences of Population Proportions. The organizing phase for analyzing online postings is summarized as follows:

1. Each coder read through the transcripts for each course topic covered in the study until an overall sense of the data was obtained.
2. The researcher (one of the coders) developed a categorization matrix for each course topic covered in the study to evaluate student's conceptual understanding learned from each topic. As an example, the conceptual understanding of the topic of descriptive statistics focused on shape, center, variability, and unusual/extreme values for quantitative data sets, and typical outcomes and variability for categorical data sets (Gould & Ryan, 2013). Table 2 displays a categorization matrix that was used to understand students' conceptual learning on the topic of descriptive statistics. Each coder followed the established coding scheme when coding the online postings (Appendix F). That is, if the discussion of "skewness" or "symmetry," for instance, were not mentioned in describing the shape of the distribution of a quantitative data set, the student's concept of the shape of the distribution is considered to be vague and weak. On the other hand, if a specific shape of the distribution, a bimodal skewed distribution, for example, can be deduced from a categorical data set, it is equally considered as lack of conceptual understanding of the shape of the distribution since there is no certain ordering of categories in categorical data set. Hence, this fact renders the discussion of the shape of the distribution meaningless (Gould & Ryan).

Table 2. Categorization Matrix for Coding the Course Topic of Descriptive Statistics

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For qualitative data sets:

Center (**Typical outcomes**) should be determined by the mode. That is the category (ies) occurred the most. Comment on the possible causes and/or indications of the mode in context.

Variability should be examined through diversity. Describe the possible causes and/or indications of the variability in context.

Distribution: Data distribution should be described in context. Frequencies and relative frequencies of those categories worth mentioning should be included.

For quantitative data sets:
-- *Graphical display*

Distribution should be commented by the following three basic characteristics from a graphical display:

a. The shape is either symmetric or skewed.

b. Comment on the possible indications of the number of mounds (one, two, multiple, or none) appeared in the distribution.

c. Describe if there are any unusually large or small values found in the display.

-- *Numerical summary*

Center should be described as a typical value of a data set:

a. If the distribution is more than one mound, it is not suitable to seek a typical value for the data set. However, it might make sense to find a typical value for each subgroup.

b. When the distribution is symmetric, the balancing point, or, the *mean*, is the center.

c. When the distribution is skewed, the halfway point, or the *median*, is the center.

Table 2 (cont'd). Categorization Matrix for Coding the Course Topic of Descriptive Statistics

d. The context of the data should be included when reporting the center of the data so that the reader understands what has been measured. For instance, the typical price of gas per gallon at the gas stations in Torrance, CA is $3.85 on this particular day. As in another example, the typical median sales price for homes in New York for July to September 2012 was $1,140,000.
Variability:
a. Informally, the variation of a data set can be measured by the horizontal spread of the data distribution.
b. When the data distribution is fairly symmetric, *standard deviation* is used to measure the variation. Specifically, the standard deviation measures the typical distance of the observations from the mean. This measure of variability provides the information whether most observations are close to the typical value or far from it.
c. When a distribution is skewed, *IQR* (Inter-quartile range) is an appropriate measure of variation. The IQR measures the space the middle 50% of the data occupy. For example, for IQR = 10.5 inches, it means that the middle 50% of the kids in the data set had heights that varied by as much as 10.5 inches.
Unusual/Extreme Values:
a. For a somewhat symmetric distributed data set, the observation is considered to be unusual when the standardized score (*Z*-score) is greater than 2 or less than -2. *Z*-score measures the number of standard deviations an observation is away from the typical value (mean). When an observation is more than two standard deviations above (*Z*-score > 2) or below (*Z*-score < -2) the mean, the observation is considered to be unusual.
b. The observation is considered to be a potential outlier when it is either smaller than 1.5 times of IQR below the first quartile (Q1) or greater than 1.5 times of IQR above the third quartile (Q3). That is, if an observation falls beyond the interval of (Q1 – 1.5 * IQR, Q3 + 1.5 * IQR), it is considered to be a potential outlier of the entire data set.

3. For the training purpose, two coders met and coded 10% of the postings for each course topic to reach the agreement about the criteria of categorization. Each coder then coded the remaining 90% according to the agreed criteria of categorization.
4. After the completion of coding for each discussion topic, individual coders re-coded a random selection of postings that consisted of 10% of each discussion topic. The number of agreements was counted and divided by the total number of postings sampled in each course topic to obtain the intra-coding agreement rate (Harwood & Garry, 2003).
5. After the completion of coding for each discussion topic, two coders reconvened to determine the inter-coding agreement rate. The inter-coding agreement rate was computed by dividing the number of agreements between the two coders by the number of coding decisions. This was measured on a category-by-category basis so that the weak reliability of any individual category would not be hidden in an overall measurement (Hardwood & Gary, 2003). Two coders discussed and negotiated for all the disagreed coding decisions. The inter-coding rate was computed and reported again after this round of discussion.

Content analysis was conducted on interview data as well. The procedure for analyzing the interview data involved the same three phases as for analyzing online postings: preparation, organizing, and reporting. The unit of analysis for analyzing interview data was each participant's entire interview. The unit of meaning was the response to each part of the interview question. The specific steps for analyzing interview data involved in the preparation phase were the same as for analyzing online postings.

Since interviews were performed in writing on *Etudes*, the transcripts of the interviews for all eight participants were downloaded directly from *Etudes*. Specifically, the steps for analyzing interview data involved in the preparation phase were as follows:

1. Interview for each participant was conducted in writing on Etudes. Transcripts of the interview data for all eight participants were downloaded from Etudes and saved in one file.
2. The names of the participants were removed and pseudonyms were assigned prior to the coding process.
3. Two copies of the interview data transcripts were prepared for the two coders for coding.

The organizing phase for analyzing interview data is summarized as follows:

1. Each coder read through the transcripts of the interview data until an overall sense of the data was obtained.
2. The researcher (one of the coders) developed a categorization matrix for each set of interview data. Take the scenario given in Appendix D as an example; Part 1 asked the participant to describe the statistical analysis process deemed as appropriate to investigate such claims. One possible statistical process that can be used to investigate such claims is through hypothesis testing. That is, one could use the statistical procedure of hypothesis testing to understand if women, on average, speak more words per day than men. Since the number of words was measured for men and women, the variable of interest is the number of words, which is a quantitative variable. Therefore, it suggests that we need to test the difference of the mean number of words spoke between men and women.

Specifically, we want to test if, on average, the women's mean number of words used is greater than the men's mean number of words used per day.

In Part 2 of the same interview question, the researcher in one study conducted a hypothesis test to investigate if the mean number of words used per day by men at a certain university differs from 7,000 words. From the *StatCrunch* printout, we see that the mean number of words used per day from a sample of 20 men at that university was 12,866.7 words, which represents about 3.15 standard errors above the hypothesized mean of 7,000 words per day. Consequently, the *p*-value is quite low at 0.0053. This *p*-value tells us that if men really uses 7,000 words per day, the probability of men using as many as 12,866.7 words or more from the hypothesized 7,000 words than 12,866.7 words per day is 0.0053. This is a rather small probability, which suggests that if the null hypothesis is true, the outcome is surprising. We therefore reject H_o and conclude that the mean number of words used per day by men at this university should be different from 7,000 words.

A categorization matrix used to evaluate student's conceptual understanding in terms of statistical literacy, reasoning, and thinking for the scenario given in Appendix D was developed and presented in Table 3. Each coder followed the established coding scheme when coding the interview data transcripts.

Table 3. Categorization Matrix for Coding the Interview Data for the Scenario Given in Appendix D

Statistical Literacy:

- The mentioning of a **statistical analysis procedure** – For example, hypothesis testing

- Showing **data consciousness** – For example, "the variable of interest is the number of words, which is a quantitative variable"

- Understanding **terminology** – For example, understanding what *p*-value is, "This *p*-value tells us that if men really uses 7,000 words per day, the probability of men using as many as 12,866.7 words or more from the hypothesized 7,000 words than 12,866.7 words per day is 0.0053."

- Being able to **interpret in non-technical terms** – For example, interpreting the conclusion from the hypothesis testing, "the mean number of words used per day by men at this university should be different from 7,000 words."

Statistical Reasoning:

- Understanding statistical processes and being able to use *p*-value to interpret the results – The response to Part 2 of the interview question demonstrates the ability of statistical reasoning (See page 73).

Statistical Thinking:

- Being able to view the entire statistical process as a whole and investigate the issues from the context of a problem – The response to Part 1 of the interview question demonstrates the ability of statistical thinking (See pages 72 & 73).

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3. For the training purpose, two coders coded 10% of the interview data together to reach the agreement about the criteria of categorization. Each coder then coded the remaining 90% according to the agreed criteria of categorization.

   After the completion of coding, individual coder re-coded a random selection of three interviews; one from each course topic of regression analysis, inferring on population means, and inferring on population proportions. The number of agreements were counted and divided by the total number of interviews sampled in each course topic to obtain the intra-coding agreement rate.

4. After the completion of coding, two coders reconvened to determine the inter-coding agreement rate. Inter-coding agreement rate was computed by dividing the number of agreements between the two coders by the number of coding decisions. Again, this was measured on a category-by-category basis to reveal the possible weak reliability of any individual category. Two coders discussed and negotiated for all the disagreed coding decisions. The inter-coding rate was computed and reported again after this first round of discussion.

In addition to qualitatively analyzing the collected qualitative data through content analysis, two statistical tests were performed for the purpose of quantitatively analyzing the coding results obtained fro each course topic. The two statistical tests performed were χ^2 independence test and two-tailed proportion *Z*-test. Specifically, the χ^2 independence tests were conducted to understand how implementing Merrill's First Principles of Instruction was related to the level of understanding for each course topic as well as all the topics combined. The two-tailed proportion *Z*-tests, on the other hand, were

conducted to compare the achievements of clear understanding over time from weekly discussions to topical project for each course topic as well as for all the topics combined.

Presentation of Results

To answer the research questions, the results from qualitative data analysis were presented using tables, appendices, and narrative descriptions. As recommended by Polit and Beck (as cited in Elo & Kyngäs, 2007), linking study results with the original data is vital in increasing the reliability of the study. Appendices and summarized tables displaying categorization matrices were used to demonstrate the links between the data and the study results. In addition, a narrative description of each category was supported by direct quotes obtained from the online postings and interview data to illustrate participant's conceptual understanding in terms of statistical literacy, reasoning, and thinking. Tables were used to present the quantitative analysis results.

Resource Requirements

The following resources were employed to complete the investigation:

1. Social networking sites: Real-life whole tasks were designed based on the information generated from social networking sites such as *Facebook* and *YouTube*.
2. *StatCrunch*: The web-based social data analysis site was used as a statistical tool for the students when analyzing data.
3. Etudes: Etudes, stands for Easy-to-Use-Distance-Education-Software, is an online learning management system (LMS) supported by the non-profit organization Etudes, Inc. Etudes was the course website where all the participants collaborated, discussed, and critiqued.

- http://www.indiana.edu/~edsurvey/evaluate/: A website where the web version of TALQ (teaching and learning quality) instrument can be viewed. TALQ instrument was used to evaluate the proposed instructional design from student's perspective.

4. ARTIST (Assessment Resource Tools for Improving Statistical Thinking) website (https://app.gen.umn.edu/artist/): The website provides a variety of assessment resources for teaching first courses in statistics. As suggested by Frick et al (2009), TALQ scales can be served as a baseline for course evaluation to accompany objective assessments of student learning comprehension (statistical literacy, reasoning, and thinking in this case). The modified Comprehensive Assessment of Outcomes in a first Statistics Course (CAOS) test instrument developed by the team was used as a final assessment to objectively assess student's learning of statistical reasoning and thinking.
5. Introductory Statistics: Exploring the World through Data (Gould & Ryan, 2013): Instructional instances were developed based on the content of this textbook.
6. The Basic Practice of Statistics (Moore, Notz, & Fligner, 2013) and Statistics, Learning from Data (Peck, 2014): Interview questions were adapted from these textbooks to assess students' cognitive process of thinking statistically.
7. Two independent coders: In the process of content analysis, a second coder is necessary to increase the reliability of coding. In addition to the

researcher, two coders were recruited to assist the researcher in analyzing qualitative data collected from various course topics. The selection of the independent coders was reviewed through interviews. Candidates included former students of the researcher as well as those recommended by colleagues who teach statistics. Qualified coders were selected based on their strong academic and research background in statistics. The coding of qualitative data collected for each course topic was completed by the researcher and one of the recruited coders.

8. Approvals from Nova Southeastern University and study site: Institutional Review Board (IRB) approval from Nova Southeastern University and approval letter from study site were obtained and attached respectively in Appendix G and Appendix H.

Barriers and Issues

Students who take the introductory statistics course at two-year community colleges are usually taking the course for the purpose of transferring to four-year colleges. Although prerequisite of successfully passing intermediate algebra is compulsory, many students taking the introductory statistics course have weak mathematics background. Therefore, it is challenging to impose student's statistical literacy and statistical thinking when teaching introductory statistics at two-year community colleges with a diverse student mix. It was documented in David and Brown (2010) that when faculty of the Department of Mathematics and Statistics at the University of Canterybury (UC) in New Zealand redesigned the entry-level statistics course that served about one-quarter of all the first-year UC undergraduates (about 1000 students) majoring in business and science

related fields in 2008, the emphasis was placed on teaching critical thinking. The newly designed instruction motivated students enrolled in the course to engage themselves in learning. Nonetheless, students who were not self-directed and who took the tutorials did not benefit from the instructional materials. Therefore, well-designed instruction is not a guarantee to student's success in learning if the student lacks motivation.

Designing instruction for the purpose of developing student's ability to think statistically at the appropriate level was another challenge. In particular, finding suitable online social sites that produce data that could be used for statistical analysis in a meaningful way was not easy. Moreover, the designing of the whole tasks was time consuming. Three real-world whole tasks were necessary for each course topic when implementing Merrill's First Principles into the instruction. Among the three tasks, the first was given as an example in the weekly module to demonstrate the task; the second was designed and assigned in weekly discussion forum for students to practice the task; the third was designed and given in the project to assess students' learning.

The work of data collection and analysis was daunting given the qualitative nature of the approach. Using multiple sources of evidence with a purpose of corroborating the same phenomenon (that is, data triangulation) enhances the construct validity, one of the criteria for having good quality of a research design. The common sources of evidence for case study research include direct observations, interviews, archival records, documents, participant-observation, and physical artifacts (Yin, 2009; 2012). The main sources of data that were collected in the study were obtained through online postings in the weekly discussion forums and three topical projects. Data collected from open-ended interviews conducted at the end of the study were also used toward the understanding of

the effectiveness of the implementation of First Principles of Instruction. Content analysis, which involves several stages, was also used as suggested by Oncu and Cakir (2011).

Summary

Presented in this chapter was a descriptive case study design that was used to describe how the implementation of Merrill's First Principles of Instruction affects students' statistical reasoning and thinking when taking introductory statistics course at a two-year community college. Specifically, the researcher designed and delivered a hybrid online introductory statistics course using real data generated from social networking sites as well as technology provided by an online social data analysis site, *StatCrunch*. The assurance of the quality was also discussed through the description of reliability and validity. The strategies for improving reliability and validity were thoroughly described. The analysis and presentation of the qualitative and quantitative aspects of the study were depicted. Resources that were required for the design of the study were noted. Finally, barriers and issues that the researcher encountered during the study design were also illustrated.

Chapter 4

Results

Introduction

The goal was to understand how the course design based on First Principles of Instruction could facilitate tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. As stated in Chapter 3, a total of 30 students consented to the study. However, due to student attrition during the semester, the semester ended with eight active students. Therefore, only data collected from the final eight participants who completed the entire course work and received a course grade were analyzed to understand participants' development of conceptual understanding of the course materials over time. Both quantitative and qualitative data were collected and analyzed. Data analysis results are presented in this chapter. While numerical data analysis was performed to analyze the results from the TALQ survey and CAOS assessment, content analysis was used to analyze the online weekly discussions, topical projects, and interviews. In addition, the numerical data analysis was also conducted on the coding obtained from content analysis.

Quantitative Data Analyses and Findings

Quantitative data include data obtained from the TALQ survey and CAOS assessment. Summary statistics of the TALQ survey data organized in terms of the nine self-report scales (Academic Learning Scale, Learning Scale, Learner Satisfaction Scale, First Principles of Instruction – Authentic Problems Scale, First Principles of Instruction

– Activation Scale, First Principles of Instruction – Demonstration Scale, First Principles of Instruction – Application Scale, First Principles of Instruction – Integration Scale, and Pebble-in-the-Pond Approach Scale), two self-report ratings (Global Rating, and Class Rating), self-report course mastery score, and objectively assessed course mastery score (CAOS) are reported in Table 4. Summary statistics of five self-report miscellaneous items are reported in Table 5. The five-point Likert scale, with 5 indicating Strongly Agree and 1 indicating Strongly Disagree, was used for all the survey items except for class rating and self-report course mastery score. Class rating and self-report course mastery score were rated using 10-point Likert scale with 10 indicating outstanding class rating and high course mastery, and 1 indicating poor class rating and low course mastery, respectively.

Table 4. Summary Statistics of TALQ Survey Data and CAOS Scores

Categories*	Mean	Standard Deviation
TALQ Scales		
Academic Learning Scale	4.3	0.41
Learning Scale	3.75	0.87
Learner Satisfaction Scale	4.375	0.35
First Principles of Instruction		
- Authentic Problems Scale	4.45	0.33
- Activation Scale	4.075	0.21
- Demonstration Scale	4.385	0.18
- Application Scale	4.5	0.4
- Integration Scale	4.275	0.43
- Pebble-in-the-Pound Approach	4.125	0.64
Global Rating	4.4175	0.61
Class Rating	8.125	1.64
Self-report Course Mastery Score	5.75	1.49
CAOS Score	73	11.75

* Except for class rating and self-report course mastery score using 10-point Likert scale, all other items of TALQ survey were rated using five-point Likert scale. The maximum score of CAOS test was 100.

Table 5. Summary Statistics of TALQ Survey Miscellaneous Items

Miscellaneous Items	Mean	Standard Deviation	Maximum	Minimum
This course is one of the most difficult I have taken.	3.625	1.19	5	2
Technology used in this course helped me to learn instead of distracting me.	4.25	0.71	5	3
This course increased my interest in the subject matter.	4.125	0.83	5	3
Opportunities to practice what I learned during this course were consistent with how I was formally evaluated for my grade.*	4.125	0.83	5	3
I enjoyed learning about this subject matter.	4.375	0.74	5	4

* This item was originally negatively worded in the survey. Mean and standard deviation were calculated based on reversed ratings to reflect its positive meaning.

TALQ Survey Results

Comparing Academic Learning Scale, Learning Scale, and Learner Satisfaction Scale (Table 4), Learner Satisfaction Scale has the highest mean rating of 4.375 (SD = 0.35) indicating that, on average, the participants in the study agreed that they were satisfied with this course. Academic Learning Scale has the mean rating of 4.3 (SD = 0.41) indicating that, on average, the participants agreed that they put a great deal of effort and time into this course. Learning Scale, on the other hand, received the lowest mean rating of 3.75 (SD = 0.87) compared to the Learner Satisfaction Sale and the Academic Learning Scale. However, the mean rating of 3.75 indicates that, generally, participants held a near agreement with the statement "I learned a lot in this course."

Six scales are related to the implementation of First Principles of Instruction. The mean ratings of the six scales related to the implementation of First Principles of Instruction range from 4.075 to 4.5 showing participants' agreement with the implementation of Merrill's First Principles of Instruction in the course design in general. In particular, Application Scale received the highest mean rating of 4.5 (SD = 0.4) showing that participants agreed nearly strongly that they were given opportunities to practice what they have learned in the course and their course instructor provided them with appropriate feedback whenever necessary. With a mean rating of 4.45 (SD = 0.33), The Authentic Problems Scale indicates participants' agreement on learning and working on authentic tasks. Demonstration Scale (Mean = 4.385 and SD = 0.18) rates the inclusion in the course design to demonstrate skills students expected to learn. The Integration Scale (Mean = 4.275 and SD = 0.43) result shows that the participants agreed that the course design allowed them to discuss and defend what they learned in the

course. In addition, the course design allowed them to apply what they learned in the course to real life situations. Although the Activation Scale received the lowest mean rating of 4.075 (SD = 0.21) among all the scales related to the implementation of First Principles of Instruction, on average, participants agreed that they had a chance to recall and apply past experience to connect to the new knowledge and skills they were learning. Finally, the Pebble-in-the-Pond Approach Scales summarizes the overall course design of implementing Merrill's First Principles of Instruction by surveying this one question, "My instructor gradually reduced coaching or feedback as my learning or performance improved during this course." Out of a total of eight participants, seven strongly agreed or agreed with one participant held neutral agreement of the approach, which rendered a mean rating of 4.125 (SD = 0.64).

Both Global Rating and Class Rating evaluate the overall quality of the course and the instructor. While Global Rating was rated from 1 to 5, Class rating was rated from 1 to 10. Participants agreed (with a mean Global Rating of 4.4175 and SD of 0.61) that the overall quality of the course and the instructor were outstanding. When cross-examined by the Class Rating, the mean Class Rating of 8.125 (SD = 1.64) indicates that, on average, the participants considered the class as a great class, which agrees with the Global Rating result. When asked about the course grade one expected to receive (not shown in Table 4), six of eight participants expected to pass with a C or above while two participants replied "Don't Know." Finally, participants evaluated their own course mastery with respect to achievement of objectives of the course. On a scale from 1 to 10, with 1 indicating a low master, 5 indicating a medium master, and 10 indicating a high master, the mean Self-report Course Mastery Score was 5.75 (SD = 1.49), indicating that,

on average, participants evaluated themselves as medium masters of the course. The mean objectively assessed course mastery scores (CAOS) of 73 (SD = 11.75) supports the self-reported medium course mastery.

The summary statistics of five miscellaneous items surveyed through the TALQ survey are recorded in Table 5. On average, participants agreed with the items "Technology used in this course helped me to learn instead of distracting me." (Mean = 4.25 and SD = 0.71), "This course increased my interest in the subject matter." (Mean = 4.125 and SD = 0.83), "Opportunities to practice what I learned during this course were consistent with how I was formally evaluated for my grade." (Mean = 4.125 and SD = 0.83), and "I enjoyed learning about this subject matter." (Mean = 4.375 and SD = 0.74). On the issue of "most difficult course I have taken," however, the mean dropped down to 3.625 with a somewhat higher standard deviation of 1.19, comparing with the other survey items. The relatively high variation of agreement on the issue of "most difficult course I have taken" indicates that not all the participants considered the introductory statistics course as the most difficult course they have taken. The ratings ranged from as low as 2 (Disagree) to as high as 5 (Strongly Agree). In summary, participants, on average, agreed or strongly agreed with all the nine scales in TALQ survey except a somewhat higher variation on the issue of Learning Scale. Some participants expressed their concerns of not having adequately learned the course. This result explains an average of a medium course master self-evaluation result, which, in turn, supported by the mean objectively assessed course master CAOS score of 73. As for the concern of the difficulty level of the course, since not all the participants surveyed considered this course as the most difficult course they have taken, this could be an indication that the

course design of implementing Merrill's First Principles of Instruction helped some students in learning in a positive way and reduced the difficulty level in the process of learning. However, this cannot be verified since the study design was an observational case study, no causation can be concluded.

TALQ Scales vs. CAOS

Regression analyses on the TALQ scales and the CAOS score revealed no significant correlations between First Principles of Instruction Scales and CAOS score. However, significant linear correlations were found between Academic Learning Scale, Learning Scale, and CAOS score (Table 6). Specifically, a statistically significant linear correlation of 0.76 (p-value < 0.05) between Academic Learning Scale and Learning Scale indicates that the self reported time and effort the surveyed participant put into the learning of the course was positively correlated to the surveyed participant's self report level of learning achievement. That is, on average, the more time and effort invested into the learning, the higher agreement on increasing the knowledge of the subjects learned. The Academic Learning Sale and the CAOS score were also found to be significantly positively correlated with a linear correlation coefficient of 0.72 (p-value < 0.05). The high linear correlation between the two items suggests that, in general, the more time and effort the participant invested into the course, the higher the CAOS score. Although the linear correlation (0.60) between academic Learning Scale and self-report course mastery score was found statistically insignificant (p-value > 0.05) (Table 6), it is worth mentioning that the effect of statistical significance may not be able to detect due to the small sample size. A linear correlation of 0.60 between the Academic Learning Scale and self-report course mastery score indicates that, on average, the more time and effort the

survey participant put into the course, the higher the participant's self-report course mastery score.

Table 6. Correlations* between Academic Learning Scale, Learning Scale, Self-report Mastery Score, and CAOS score

	Academic Learning Scale	Learning Scale	Self-report Course Mastery Score	CAOS Score
Academic Learning Scale	--	**0.76 (0.03)**	0.60 (0.11)	**0.72 (0.04)**
Learning Scale	**0.76 (0.03)**	--	0.39 (0.34)	0.49 (0.22)
Self-report Course Mastery Score	0.60 (0.11)	0.39 (0.34)	--	0.36 (0.38)
CAOS Score	**0.72 (0.04)**	0.49 (0.22)	0.36 (0.38)	--

* Table displays correlation coefficient (*p*-value) between pairs of two items. Significant correlations are displayed in bold.

In summary, the Academic Learning Scale is positively correlated to Learning Scale, self-report course mastery score, and CAOS score. The results show that, on average, the more time and effort the surveyed participant reported to spend in the course, the higher agreements on gaining more knowledge from the course and achieving a higher-level of self reported mastery of the course, and the higher objective CAOS score in the final course assessment.

Qualitative Data Analyses and Findings

Qualitative data include data collected from online weekly discussions, topical projects, and interviews. Content analysis was conducted in analyzing these data qualitatively. This section begins with the quantitative descriptions of intra-coding and inter-coding agreement rates of the collected qualitative data. Next, statistical tests results (independence tests and Z-tests) on coding results collected through content analysis from weekly discussions and topical projects were analyzed for an understanding of the overall effectiveness of implementing Merrill's First Principles of Instruction. Percentages of "clear understanding" coding from interviews were also calculated and analyzed. Finally, a detailed description of cognitive development toward conceptual understanding based on a purposeful sample of four students selected from the final eight active participants was presented in accordance with statistical literacy, reasoning, and thinking to reflect the goal of this study.

Intra-coding Agreement Rates

Intra-coding agreement rate measures the coder agreement with oneself over time. While the researcher (Coder #2) coded the weekly discussions, topical projects, and interview data for the entire studied period, two research assistants assisted the researcher

and shared the coding work. Coder #1 coded the weekly discussions and topical projects for the topics of Descriptive Statistics and Regression Analysis, and interviews. Coder #2 coded the topics of Sampling & Inferences on Population Means and Sampling & Inferences on Population Proportions. Table 7 shows the intra-coding agreement rates for eight participants who completed the semester-end CAOS tests as well as TALQ surveys of their weekly discussions, topical projects, and interview data by each coder. The overall intra-coding agreement rates of all the coders for the entire study period ranged from 85% to 100% with two intra-coding agreement rates falling below 90% (85% and 87%).

Table 7. Intra-coding Agreement Rates by Each Coder

Course Topic	Coder	Intra-Coding Agreement Rate (Number of Agreements/Total Items)
Weekly Discussions and Topical Projects:		
Descriptive Statistics	Coder #1	85% (41/48)
	Coder #2	94% (45/48)
Regression Analysis	Coder #1	95% (63/66)
	Coder #2	98% (65/66)
Sampling & Inferences on Population Means	Coder #3	92% (101/110)
	Coder #2	97% (107/110)
Sampling & Inferences on Population Proportions	Coder #3	100% (60/60)
	Coder #2	95% (57/60)
Open-ended Interviews:		
Interviews	Coder #1	87% (26/30)
	Coder #2	93% (28/30)

Inter-coding Agreement Rates

Inter-coding agreement rate measures the agreement between two coders. Tables 8 and 9 show the first-round inter-coding agreement rates by category coded for the eight finalists of their weekly discussions and topical projects, and interview data, respectively. For the first round, the two coders' agreement on all the categories ranged from 86% to 100% with an overall agreement rates ranged from 93% to 98% on four course topics. After discussing and negotiating for all the disagreed coding decisions, the coders reached to 100% inter-coding agreement rate for each category. Two items of the interview data failed to reach 100% agreement rates for the first round of coding. After reconvening, the two coders reached to 100% agreement rates.

Table 8. Inter-coding Agreement Rates on Weekly Discussions and Topical Projects by Category

Course Topic/Category	Inter-Coding Agreement Rate
Descriptive Statistics	93% (180/194)
Quantitative Data Sets	93% (132/142)
Distribution	94% (49/52)
Center	86% (18/21)
Variability	90% (19/21)
Unusual/Extreme Values	96% (46/48)
Qualitative Data Sets	92% (48/52)
Typical Outcomes	96% (25/26)
Variability	88% (23/26)
Regression Analysis	94% (207/221)
Scatterplot	96% (74/77)
Scatterplot	97% (32/33)
Unusual Values/Outliers	95% (42/44)
Correlation	86% (19/22)
Correlation Coefficient	86% (19/22)
Regression	93% (114/122)
Regression Model	93% (56/60)
Prediction	93% (41/44)
Coefficient of Determination	94% (17/18)

Table 8. (Cont'd) Inter-coding Agreement Rates on Weekly Discussions and Topical Projects by Category

Course Topic/Category	Inter-Coding Agreement Rate
Sampling & Inferences on Population Means	98% (139/143)
Sample Mean Distribution	97% (139/143)
Sample Distribution	97% (65/67)
Sampling Distribution	97% (74/76)
Confidence Interval of Population Mean	96% (69/72)
The Basics	93% (25/27)
Eligibility	100% (30/30)
Interpretation	93% (14/15)
Hypothesis Test on Population Mean	95% (163/171)
The Basics	100% (27/27)
Hypotheses	94% (45/48)
Testing	94% (30/32)
Eligibility	94% (30/32)
Results/Interpretation	97% (31/32)

Table 8. (Cont'd) Inter-coding Agreement Rates on Weekly Discussions and Topical Projects by Category

Course Topic/Category	Inter-Coding Agreement Rate
Comparison of Two Population Means	94% (67/71)
The Basics	96% (23/24)
Independence vs. Dependence	100% (7/7)
Testing vs. Confidence Interval	86% (12/14)
Results/Interpretation	96% (25/26)
Sampling & Inferences on Population Proportions	95% (361/381)
Sample Proportion Distribution	94% (120/128)
The Basics	
Sampling Distribution	
Confidence Interval of Population Proportion	81% (26/32)
Eligibility	93% (13/14)
Confidence Level Selection	100% (11/11)
Interpretation	100% (8/8)

Table 8. (Cont'd) Inter-coding Agreement Rates on Weekly Discussions and Topical Projects by Category

Course Topic/Category	Inter-Coding Agreement Rate
Hypothesis Test on Population Proportion	97% (152/156)
The Basics	96% (23/24)
Hypotheses	100% (48/48)
Testing	96% (23/24)
Eligibility	97% (29/30)
Results/Interpretation	97% (29/30)
Comparison of Two Population Proportions	97% (62/64)
The Basics	96% (27/28)
Independence vs. Dependence	100% (8/8)
Testing vs. Confidence Interval	100% (14/14)
Results/Interpretation	93% (13/14)

Table 9. Inter-coding Agreement Rates on Interview Data by Category

Category	Inter-Coding Agreement Rate
Statistical Literacy	97% (62/64)
Data consciousness	100% (8/8)
Statistical Concepts	88% (7/8)
Statistical terminology	88% (7/8)
Data Collection	100% (8/8)
Generating descriptive statistics	100% (8/8)
Interpretation/communication in layman's terms	100% (8/8)
Statistical Reasoning	100% (16/16)
Understanding process	100% (8/8)
Being able to interpret the statistical results	100% (8/8)
Statistical Thinking	100% (16/16)
Being able to view the entire statistical process	100% (8/8)
Knowing how/what to investigate through the context	100% (8/8)

Statistical Tests Results

For the purpose of evaluating the effectiveness of implementing Merrill's First Principles of Instruction in promoting conceptual understanding, two statistical tests, namely, chi-square independence test (χ^2 -test) and two-tailed proportion *Z*-test were conducted on each course topic as well as all the topics combined. Chi-square independence tests (χ^2 -tests) were performed to first examine whether implementing Merrill's First Principles of Instruction (explanatory variable) was related to the level of understanding (response variable) when learning Introductory Statistics. The explanatory variable, the implementation of Merrill's First Principles of Instruction, was described by the assignment type (weekly discussions and topical project) while the response variable, level of understanding, was classified by three levels of understanding (none, vague, and clear). According to the Pebble-in-the-Pond framework, an example was first demonstrated in the weekly module. A question similar to the example given in the module was assigned in the weekly discussions with reduced guidance followed by a third similar question with the minimum guidance assigned in the topical project. Therefore, it is appropriate to use the assignment type to understand whether the implementation of Merrill's First Principles of Instruction could effectively increase students' conceptual learning. Next, two-tailed proportion *Z*-tests were conducted to empirically compare the achievements of clear understanding between weekly discussions and topical project for each course topic as well as for the entire course topics combined. Specifically, two-tailed proportion *Z*-tests were conducted to compare the percentages of obtaining a "clear-understanding" coding between weekly discussions and topical projects.

Table 10 shows χ^2-test and two-tailed proportion Z-test results between assignment type and level of understanding for each course topic as well as for all the course topics combined. For the topic of Descriptive Statistics, the large *p*-value (0.102) from χ^2-test indicates that the level of understanding is independent to the assignment type. That is, the implementation of Merrill's First Principles of Instruction was not related to students' understanding level when learning the topic of Descriptive Statistics. Although a significant Z-test result (*p*-value = 0.3573) of the proportions of "clear understanding" coding between weekly discussions and the topical project was not found, the sample difference shows a 9% increase in "clear understanding" coding from weekly discussions (49%) to topical project (58%). A similar no association result (*p*-value = 0.4173) between the implementation of Merrill's First Principles of Instruction and students' level of understanding appeared when learning the topic of Regression Analysis. Moreover, an insignificant (*p*-value = 0.3092) decrease of 8% of "clear understanding" coding was found from weekly discussions (53%) to the topical project (45%).

Table 10. Independence Test (χ^2-test) and Two-Tailed Proportion *Z*-test Results of Level of Understanding Explained by Assignment Type

Topic	P_1*	P_2*	P_1- P_2*	*p*-value
Descriptive Statistics	49%	58%	-9%	χ^2-test: 0.102 *Z*-test: 0.3573
Regression Analysis	53%	45%	8%	χ^2-test: 0.4173 *Z*-test: 0.3092
Sampling & Inferences on Population Means	37%	50%	-13%	χ^2-test: 0.0062 *Z*-test: 0.0088
Sampling & Inferences on Population Proportions	53%	49%	4%	χ^2-test: 0.0003 *Z*-test: 0.4034
All Topics Combined	47%	50%	-3%	χ^2-test: 0.0024 *Z*-test: 0.3894

* P_1: Proportion of "clear understanding" coding in weekly discussions.
P_2: Proportion of "clear understanding" coding in topical project

However, when the course continued, significant association (*p*-value = 0.0062) appeared on the course topic of Inferring Population Means between the implementation of Merrill's First Principles of Instruction and the level of understanding. Specifically, a statistically significant (*p*-value = 0.0088) increase of 13% in "clear understanding" coding found from weekly discussions (37%) to the topical project (50%). Put together, the implementation of Merrill's First Principles of Instruction to teach Inferring Population Means resulted in a statistically significant increase in students' understanding. There was a practical significance increase of 13% of clear understanding among the eight participants.

Significant association (p-value = 0.0003) between the implementation of Merrill's First Principles of Instruction and the level of understanding was also found on the course topic of Inferring Population Proportions. However, an insignificant (p-value = 0.4034) decrease of 4% in "clear understanding" coding was detected from weekly discussions (53%) to the topical project (49%). Although one cannot make a causal conclusion by saying that Merrill's First Principles of Instruction negatively affected students' level of understanding, one could conclude, from the results of this case study, that in learning the topic of Inferring Population Proportions, the implementation of Merrill's First Principles of Instruction was inversely related to students' level of understanding. However, the decrease of 4% in clear understanding was statistically insignificant.

When combining all course topics, a statistical significant (*p*-value = 0.0024) association between the implementation of Merrill's First Principles of Instruction and the level of understanding was revealed. Nonetheless, the increase of 3% of clear

understanding from online discussions (47%) to topical projects (50%) was statistically insignificant (p-value = 0.3894).

Finally, percentages of "clear understanding" coding in terms of statistical literacy, statistical reasoning, statistical thinking, and overall interview results were calculated and are displayed in Table 11. Recall that each participant received a different set of interview questions. Although different course topics were involved in the interview questions, the purpose of the interviews was to evaluate participants' conceptual understanding in terms of statistical literacy, statistical reasoning, and statistical thinking. The percentage of items related to statistical literacy marked as clear understanding was at the lowest of 29%, comparing with 69% of clear understanding for each of the categories of statistical reasoning and statistical thinking. That is, less than one-third of the items evaluating statistical literacy in the interviews can be considered as having clear understanding of the basic statistical skills such as data consciousness, statistical literacy, statistical concepts, and being able to interpret the statistical results using context to communicate with others. On the other hand, for every 10 items evaluating statistical reasoning and statistical thinking, almost seven items were marked as having clear understanding. The items evaluated in each category of statistical literacy, statistical reasoning, and statistical thinking are listed in Appendix I.

Table 11. Percentages of “Clear Understanding” Coding for Interviews

Categories	Frequency	Total Items	Percentage
Statistical Literacy	11	38	29%
Statistical Reasoning	11	16	69%
Statistical Thinking	11	16	69%
All Categories Combined	33	70	47%

When combining all the three categories of statistical literacy, statistical reasoning, and statistical thinking, the overall percentage of clear conceptual understanding found from the interview was 47%. Comparing the percentage of overall clear understanding found from the interview with the percentages of overall clear understanding found from weekly discussions (47%) and topical projects (50%), it can be concluded that there is no practical differences of clear understanding between during-semester training (online discussions and topical projects) and the semester-end interviews (Table 12). This result can be translated as; overall, the clear conceptual understanding had been established during the semester training and was maintained at the similar level at the semester-end interviews.

Table 12. Percentages of “Clear Understanding” Coding for Various Assessment Types

Assessment Type	Frequency	Total Items	Percentage
Weekly Discussions	216	458	47%
Topical Projects	298	598	50%
Interviews	33	70	47%

Content Analysis

The content analysis results were generated from a purposeful sample of four students selected from the final eight active participants with a consideration of their grade, gender, and most importantly, their learning process, to reflect how the course design did or did not benefit their statistical concept development over the entire study period. The sample consists of two female students and two male students. Arranged alphabetically by their pseudonyms, the four students selected are Amelia, Charlie, Harry, and Jessica.

To better understand whether Merrill's Pebble-in-the-Pond instructional approach facilitates student's conceptual understanding, findings from content analysis were discussed from each selected participant in accordance with their conceptual development related to statistical literacy and statistical reasoning. The design of the weekly discussions for each course topic allows students to know how and what to investigate by modeling after the examples given in the weekly modules. Therefore, a student's capability of thinking statistically was only evaluated through the open-ended interview because the interview question related to which course topic was not informed to the student prior to or during the interview. Merrill's Pebble-in-the-Pond instructional approach was designed into the instructional instances starting with the topic of Descriptive Statistics in the second week of the study period. Followed by the course topics of Regression Analysis, Sampling & Inferences on Population Means, and Sampling & Inferences on Population Proportions (Table 1).

Amelia.

1. Findings associated with statistical literacy

a. Data consciousness

Data Type

In the first weekly discussion assignment when learning the course topic of Descriptive Statistics, students were asked to graphically and numerically summarize the qualitative variable, Popular Week, defined as "The week when the most people were talking about this page", in a data set consisting of various responses collected from a sample of *Facebook* pages of the mosques in the United States. Stemming from the misunderstanding of the structure of the data set and a lack of solid understanding in differentiating between qualitative data and quantitative data, Amelia analyzed the variable Popular Week in terms of other quantitative variables included in the data set. Amelia posted,

> *The distribution (or values) of the data set for the variable, 'Popular Week', include the number of likes, the number of people mentioning the page and the number of photos posted on the page. Although several categories are contained within the variable 'Popular Week', the center of the variable is the number of likes received.*

The confusion on the basic understanding of the data type between qualitative data and quantitative data remained a challenge to Amelia toward the end of the semester when she discussed the choice of an appropriate test statistic in testing the population proportion. Note that standard deviation could not be found from a qualitative data set, Amelia

wrote, “Since our population standard deviation is unknown at this point, our test statistic will be …”.

Valid Data

Another issue of data consciousness was related to having the consciousness of excluding irrelevant data in the process of data analysis. In setting up a statistical process of regression analysis to answer a question concerning the linear correlation between the number of hours worked per week and the number of credit hours taken for those students who worked, Amelia used all the responses in the data set including those students who did not work. However, as time progressed, Amelia successfully showed her consciousness of including only data that were relevant to the question of concern. In her project of making inferences of her *Facebook* friends’ age, Amelia examined only those responses “where age has been reported”. When estimating the proportion of her *Facebook* friends who attended college, Amelia consciously included only friends who “have reported attending college” to show her awareness of avoiding the inclusion of irrelevant data.

b. Understanding statistical concepts and terminology

In learning the course topic of Descriptive Statistics in the beginning of the semester, Amelia showed no difficulties in differentiating the statistical terms. However, facing the many new statistical terms appeared in learning new course topics, Amelia

struggled with using the correct terms and expressing correct statistical concepts as the semester continued.

Terminology

When learning Regression Analysis, Amelia was confused with the statistical terminology of ‘no correlation’ with ‘non-linear correlation’. While ‘no correlation’ means none or little correlation between the two variables, ‘non-linear correlation’ means that the two variables are not linearly correlated but correlated in a non-linear way. The scatterplot displayed that almost no correlation found between the two variables (Figure 1). However, Amelia incorrectly commented the correlation as, “a negative, non-linear weak correlation between the age of an individual and the number of wall posts.”

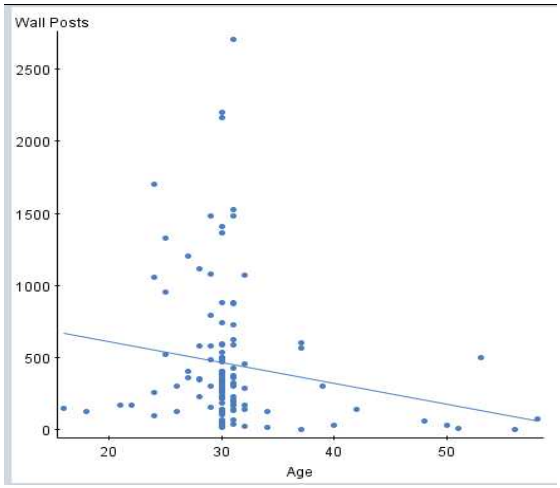


Figure 1. Scatterplot of age and wall posts of Amelia’s *Facebook* friends

Amelia showed confusion between similar terms such as sample distribution and sample mean distribution when learning the course

topics of Sampling & Inferences on Population Means and Sampling & Inferences on Population Proportions. The misusages of these terms stemmed from the confusions of the terms learned in the beginning of the semester. In Descriptive Statistics, Amelia understood clearly about the terms such as population, sample, mean, and proportion. However, Amelia later developed her own terms that were not part of the statistical terminology such as ‘population mean distribution’, ‘mean population proportion’, and ‘mean sample proportion’.

Apart from the misusages of the terms mentioned, the term ‘degrees of freedom’ was incorrectly interpreted as ‘margin of error’: “I believe the degrees of freedom (or margin of error) is large.” Therefore, Amelia interpreted the degrees of freedom of 24 as, “give or take 24 minutes”. At times, Amelia misused the term confidence level (used in constructing confidence intervals) for significance level (used in conducting hypothesis tests) and vice versa.

Statistical Concepts

An incorrect basic understanding of the term ‘level of significance’ was found in Amelia’s posting: “The level of significance is to determine the strength of our test; it is also the probability that we will make either a Type I or Type II error.” A misconception related to level of significance appeared in her weekly discussions when Amelia made a decision of a hypothesis test by comparing the *p*-value (2.6%) with the level of significance (5%): “This result indicates that we can safely

reject the null hypothesis without hesitation that we might be making a mistake." Although the null hypothesis could be rejected at a significance level of 5%, there was no guarantee that the decision of rejecting the null hypothesis was 100% correct. This insufficient conceptual understanding continued in her project discussions. "Comparing the prescribed level of significance (5%) with the actual *p*-value (< 0.0001), we can see that the actual is very low and indicates that we can safely reject the null hypothesis without risking a Type I or Type II mistake." The probability of making a Type I error or Type II error does not vanish even when the *p*-value is extremely low at less than 0.0001.

The relationship between the standard error and the precision of a confidence interval was found incorrectly stated in Amelia's project for Sampling & Inferences on Population Proportions. Although the precision of a confidence interval is inversely related to the standard error, they are not complementary as claimed in Amelia's posting, "The standard error for our sample proportion is 8%, which represents a moderately high precision (92%) in targeting the population proportion using the sample proportion produced from a sample size of 40 individuals."

c. Interpreting statistical results using non-technical and layman's terms with context

Context

Throughout the first weeks of learning the course topic of Descriptive Statistics, Amelia was struggling with the inclusion of the context when interpreting the statistical results. For instance, in the weekly discussion of analyzing the number of photos tagged to a *Facebook* page from a histogram (Figure 2), Amelia wrote, "… the majority of values (number of photos that have this page tagged) is high for the values between 0-500" when she actually meant that the majority of the mosques in the survey had 500 or fewer photos tagged on their *Facebook* pages. This same issue of lacking the context appeared in her project posting for the course topic of Descriptive Statistics. After finding an interval to determine the extremely old and young ages of her *Facebook* friends, Amelia wrote, "So, any value outside of (28.5, 32.5) of our data set is considered an outlier. There are several outliers within this data set, which makes sense based on the other analysis done above." There was no mentioning of the age when interpreting the outliers.

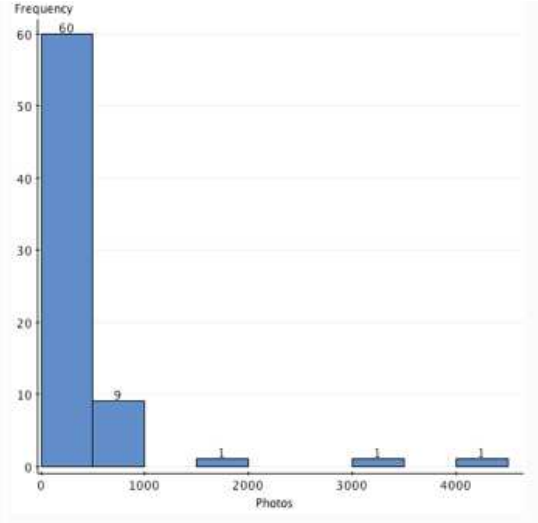


Figure 2. Histogram of the number of photos tagged on a *Facebook* page

The issue of reporting the results with no context continued in her weekly discussions when making inferences about population means. Although Amelia demonstrated good understanding of the terms used in hypothesis testing such as null hypothesis, alternative hypothesis, Type I error, Type II error, *p*-value, and level of significance, no proper context was included when making interpretations of these terms. For example, in testing the mean lecture length being longer than 80 minutes, Amelia interpreted the null hypothesis as, “the population mean is no different than 80 minutes”, and Type I error as, “if our data shows a population mean greater than 80 minutes; when in fact, 80 minutes is the true population mean.”

Non-technical Terms

In posting her weekly discussions for the topic of hypothesis testing on population proportions, the interpretation of the terms was laden with technical terms such as ‘reject’, ‘accept’, ‘null hypothesis’, and ‘fail to’. These technical terms added to the difficulty in understanding the conclusion of the statistical results. The following interpretation of the terms Type I error and Type II error was found in her weekly discussions:

> *A Type I error will occur if we reject our null hypothesis by failing to determine that 50% of the surveyed Muslim population believed the story to be false when in fact 50% is the accurate population proportion who hold this belief. A Type II error will occur if accept the determination that 50% believed the story to be false when the population proportion who came to this conclusion is not 50% and this hypothesis should be reject*.

A similar posting of the interpretation of a Type I error and Type II error was also found to be incomprehensible in Amelia’s project.

2. Findings associated with statistical reasoning

   a. Understanding statistical processes

Amelia understood the statistical processes of analyzing descriptive statistics of one variable and finding correlation between two quantitative variables. However, Amelia showed difficulties in the process of making inferences on a population parameter.

Randomization and Normality Assumptions

Amelia had vague concepts about the randomization and normality requirements for conducting inferential statistical analysis. When commenting on the randomization requirement for estimating a population mean in her weekly discussions, Amelia stated, “We would not be able to construct a confidence interval if our data was not collected through voluntary surveys or other reliable methods – because no methods for determining the confidence intervals exist in this case.” Unlike what Amelia commented, a confidence interval could be found even if data were from a non-random sample. However, the statistical results obtained could not be inferred to the entire population. As for the normality requirement, it refers to the requirement of the sample mean distribution being somewhat symmetric. One of the possibilities for a sample mean distribution to be symmetric is, according to the Central Limit Theorem, when the distribution of the population where the samples are drawn from is symmetric. However, Amelia quoted the other way around, “Based on the Central Limit Theorem, if the sample mean distribution shape is symmetric, it can be assumed that the population distribution shape will also be symmetric.” This same mistake was also found in her project.

A similar normality assumption was required in making inferences of comparing two population proportions. The normality assumption includes the fulfillment of large samples (at least 10 successes and 10

failures in each sample) and big populations (population size should be at least 10 times of its sample size). In the project, Amelia compared the proportions of liking a book between her male and female *Facebook* friends through conducting a hypothesis test. Prior to the test, Amelia mistakenly concluded that both of the requirements were satisfied when there were only seven successes (providing the title of the book liked) in the sample of her male *Facebook* friends. Using a sample size of 50 male friends, Amelia needed to have at least 500 male *Facebook* friends. With a total number of 414 *Facebook* male and female friends, unless sampled with repetition, the big population requirement could not be satisfied.

Level of Significance

In discussing the choice of a significance level for testing a population proportion in her weekly discussions, Amelia wrote, “Since our population size is pretty small, it’s important to not have a significance level that is too high or too low.” Firstly, the size of the population was large since the population associated with the survey consists of all the Muslims in 27 countries. Secondly, the choice of significance level is not related to the population size. Rather, the choice of the significance level is related to the consideration of the probability of making a Type I error or Type II error. Choosing a lower significance level restricts the chance of making a Type I error, unlike what Amelia claimed, “Our likelihood of making a Type I error increases if the level

is too low." Although Amelia no longer linked the significance level to the population size in her project posting, the choice of significance level at 5% was not theoretically justified. Amelia understood that the level of significance was used to represent as a standard "to determine whether to reject the null hypothesis or not." However, she contradicted the purpose of the level of significance by saying, "I have chosen this based on the moderate requirement that we do not want to commit a Type I error by rejecting the null hypothesis in error, when in fact it is true." By choosing the level of significance at 5%, one allows up to 5% chance of committing a Type I error. If one is serious in avoiding making a Type I error, a lower level of significance, for example, 1%, should be used instead of 5%.

Estimating 'Mean' Proportion

When estimating the proportion of her *Facebook* friends who reported having attended college in the project, Amelia was supposed to construct a confidence interval for the population proportion of her *Facebook* friends who reported having attended college. However, stemmed from the lack of data consciousness between the mean (quantitative data) and the proportion (qualitative data), Amelia constructed a 95% confidence interval for the 'mean population proportion' of her *Facebook* friends who reported having attended college. The interval was constructed by treating the sample proportion of 50% of her *Facebook* friends who reported having attended college as

the sample mean. Amelia made the same mistake of treating the sample proportion of her *Facebook* friends residing in Los Angeles (11%) as the sample mean when conducting a hypothesis test in her project. Continued with the confusion between the mean and the proportion, Amelia incorrectly set up the statistical procedure to test the difference of two 'mean' proportions between her male and female friends. Hence, the hypothesis testing was on the difference of two means rather than the difference of two proportions, which contributed to invalid statistical results.

Hypothesis Test

Even though making inferences of proportion was mistaken by making inferences of mean, Amelia understood the purpose of a hypothesis test was to seek the opportunity (with significant sample evidence) to reject the null hypothesis. This correct statistical concept about a hypothesis test was shown in the following explanation, "Meaning, the assumption for our hypothesis is that 50% of the Muslims in the surveyed 27 countries considered the story to be false. We are seeking to determine whether there's evidence to conclude that more than 50% believed the story to be false."

b. Being able to interpret statistical results

In the beginning of the semester when learning the topics of Descriptive Statistics and Regression Analysis, Amelia was unsure what to look for from the statistical results produced from *StatCrunch*. She

was also confused with how to interpret the statistical results. However, Amelia showed more confidence knowing what to interpret and became more comfortable in the interpretation of the results toward the semester end when learning the topic of Sampling & Inferences of Population Proportions.

Descriptive Statistics

When analyzing the number of photos tagged on a *Facebook* page from a graphical display in the weekly discussions for the course topic of Descriptive Statistics (Figure 2), Amelia described only the shape of the data distribution. There was no mentioning of the number of mounds and no discussion on the unusually large amount of photos tagged on the *Facebook* pages. A similar discussion of the age of her *Facebook* friends through a graphical display was posted in Amelia's project. From the dotplot constructed in *StatCrunch* (Figure 3), Amelia incorrectly concluded from the dotplot display that the shape was a skewed distribution. Although there was a mentioning of having "one mound within this data set", there was no interpretation of the mound. No discussion of unusual/extreme values was reported, either.

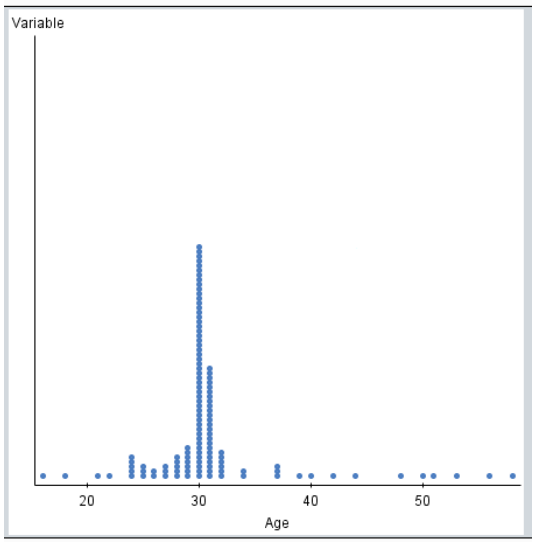


Figure 3. Dotplot of the age of Amelia's *Facebook* page

Another example showing not knowing how to interpret the statistical results appeared in Amelia's project when describing the distribution of the relationship status of her *Facebook* friends from a bar chart display (Figure 4). Amelia reported all the frequencies of the responses in different categories without summarizing the distribution and giving a meaningful interpretation in context. Amelia posted, "Distribution: The values within this data set include 1) 2 Divorced, 2) 11 Engaged, 3) 53 In a Relationship, 4) 2 It's Complicated, 5) 85 Married, 6) 1 Separated, 7) 89 Single, 8) 2 Widowed."

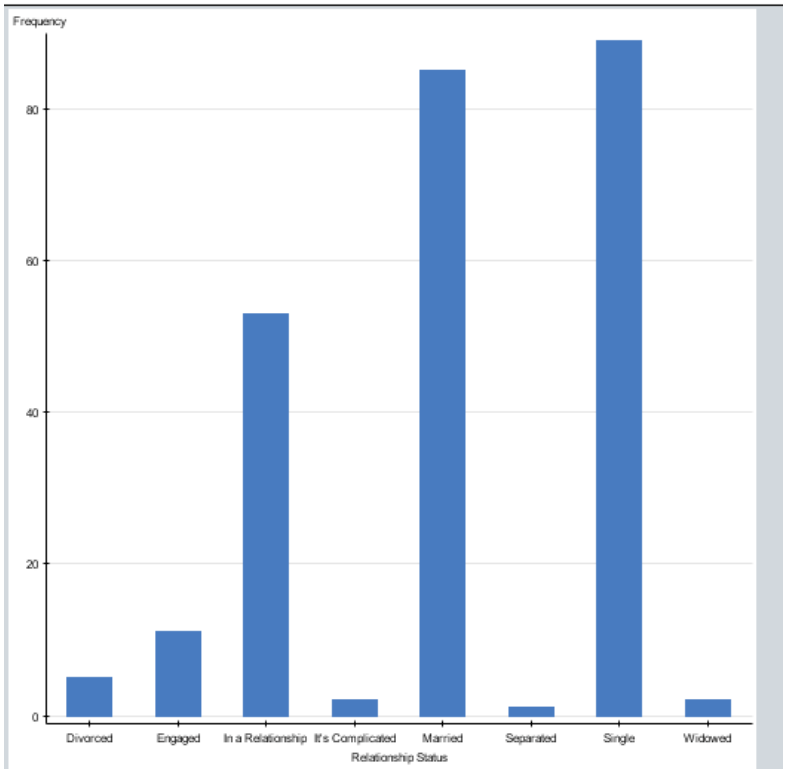


Figure 4. Bar chart of the relationship status of Amelia's *Facebook* page

The first part of the course topic of Sampling & Inferences on Population Means began with a review of sample distribution, which was covered in the first course topic of Descriptive Statistics. Each student was required to select his/her own random sample of lectures from a given *iTunes* library collection. Based on the sample selected, student conducted graphical and numerical analyses. The statistical process was completed using *StatCrunch*. According to the histogram produced (Figure 5), Amelia described the sample distribution of the lecture lengths of 25 lectures randomly selected from the entire collection as follows:

> *The sample distribution of the lecture lengths can be described by the shape of our histogram above, which is somewhat symmetric (or normal). It can also be described by the sample mean. Looking at the Summary Statistics, we see that the majority of the lectures are around 89 minutes long. The sample distribution also tells us that this can vary up to about 32 minutes in length.*

Amelia's description depicted her fragmental basic statistical concept of a data set. In addition to the incomplete statistical concept, Amelia was ambiguous when recounting the statistical terminology of mean and standard deviation.

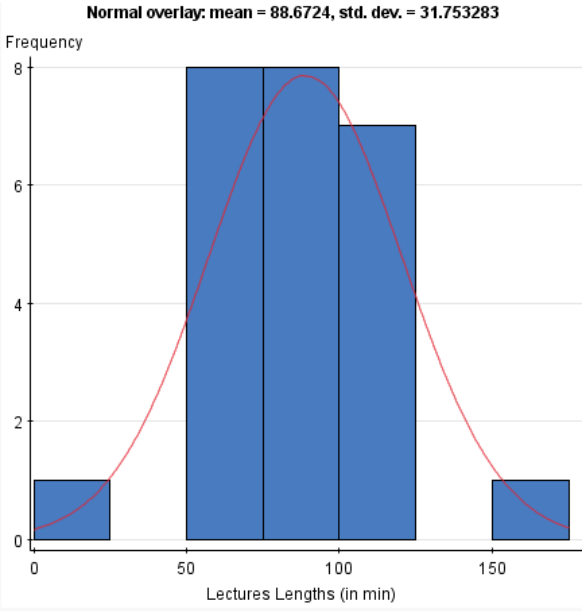


Figure 5. Histogram of Amelia's sample of lecture lengths

Regression Analysis

When learning Regression Analysis, Amelia demonstrated difficulties in recognizing the regression outliers and clusters through the scatterplot due to the misunderstanding of these statistical terms. In particular, Amelia confused the regression outliers with the outliers from a one-variable data set. Due to this confusion, in analyzing the existence of the regression outliers and the clusters from the scatterplot produced between work hours and credit hours in her weekly discussions (Figure 6), Amelia incorrectly concluded, “The student worked 44 hours per week while taking 4 credit hours in school” as a regression outlier. Amelia continued to discuss whether this regression outlier could be considered as influential, “The outlier doesn’t seem very influential in the overall trend, shape and strength of the scatterplot.” An influential regression outlier influences the strength of the correlation between the two variables, not “the strength of the scatterplot” as explained in Amelia’s posting. The underlying issue of this statement is the misconception of what a scatterplot could provide. Scatterplot is a means used to visualize the correlation between the two studied variables. It is inappropriate to discuss the trend, shape or the strength of a scatterplot. Rather, it is more suitable to analyze the trend, shape, and the strength of the correlation between the two variables. As for the clusters, it should be apparent that there were no clusters formed in the scatterplot. However, Amelia posted, “There are also a few clusters.”

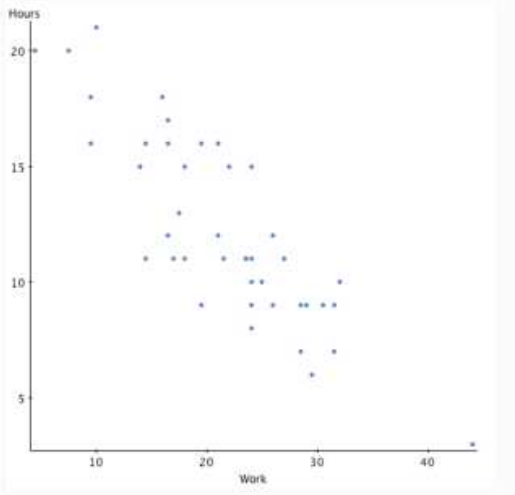


Figure 6. Scatterplot of work hours and credit hours

Amelia did not overcome the challenges of correctly recognizing the regression outliers and clusters from the scatterplot in her project discussions when she analyzed the relation between the age and the number of wall posts of her *Facebook* friends (Figure 1). In contrast to Amelia's posting, "There does not appear to be any outliers in the scatterplot", several regression outliers appeared. They were the individuals with ages around 30 and having more than 2000 wall posts. As for the clusters, unlike what Amelia claimed, "There are several clusters around the age of 30 and between 0-500 wall posts", there were two clusters found in the scatterplot produced from her *Facebook* friends. One cluster contains the majority of the observations that are following the negative trend indicating that the older the individual is the fewer number of wall posts on his/her *Facebook* page. The other cluster appeared on the scatterplot was the group of those regression outliers.

Those regression outliers were the individuals who were at the age of 30 but with many more wall posts (more than 2000) on their *Facebook* pages than the other *Facebook* friends who were at the age of 30 with fewer than 2000 wall posts on their *Facebook* pages.

In the project discussions for the topic of Regression Analysis, Amelia reported the slope and *y*-intercept of the regression model produced through *StatCrunch* with no interpretation of the terms in context. Even though the *y*-intercept of 898 had no practical meaning in context since it represented the number of wall posts on her *Facebook* friend's page when her friend was at the age of 0, there should be a mentioning in this regard. The slope of the regression model was reported as -14.42 with no interpretation in context. However, Amelia knew how to use the slope to explain the negative trend, "The slope is -14.42. This makes sense because we can see a dramatic decrease in the number of wall posts for individuals who are older than 30."

The coefficient of determination (r^2) was also incorrectly interpreted in the project. Amelia understood that r^2 measured the quality of the regression model but failed to interpret it correctly. With an r^2 of 3%, in context, it means that the percentage of the variation of the number of wall posts that can be explained by the regression model through age was only 3%. Amelia's incorrect understanding of r^2 was depicted in the following posting: "The *r*-squared for this particular

regression line is 3%, which means to predict the number of wall posts based on age using this line would be accurate only 3% of the time."

3. Findings associated with open-ended interview & summary

Amelia's open-ended interview question given at the end of the semester was related to the topic of Regression Analysis (Appendix J). Amelia's reply to the first part of the interview reflected her capability of thinking statistically. Specifically, Amelia understood that the appropriate statistical process she should employ to investigate the question assigned to her was through regression analysis.

> *Well since the values within the data set are paired and we would like to see the relationship (whether strong or weak; positive or negative, linear or non-linear) between the two values, I am thinking a regression analysis would be the best method to answer the question. For instance, I would imagine that the outcome of our results might say something like "It is typical that when a brother is 65 inches tall, his sister would usually be about 62 inches tall." or something to that effect.*

The second part of the interview evaluated the statistical reasoning ability. While her reply reflected clear understanding of the process of conducting a regression analysis, Amelia failed to correctly interpret some of the statistical results such as commenting on the existence of the regression outliers from a scatterplot, describing incorrectly the correlation as nonlinear, and interpreting incorrectly the coefficient of determination (r^2).

Based on looking at the scatterplot, it seems as though there is definitely a moderately-positive-nonlinear correlation because the dots are not forming one line; there are outliers and although the trend does not necessarily seem to move upward in a distinguishable way, it certainly does not seem to move downward. If I had to choose between positive and negative based on the scatterplot alone, I would say positive.

Also, when I review the regression model the r (correlation coefficient) reflects the same thing I was observing from the scatterplot. There is about a 55% (or, moderate but slightly positive) correlation between the heights of the brothers and the sisters.

I would not use this regression model to predict Tonya's height based on her brother Damian's height because the R-sq value is very low; the R-sq value represents the strength of the model. It is approximately 31%. This tells me that the model would likely be accurate in approximately 3 out of 10 predictions.

As for the statistical literacy, Amelia could verbalize the statistical terminology correctly except for the term "s*lightly* positive" correlation. While the magnitude of the correlation coefficient reflects the strength of the correlation, the sign of the correlation coefficient portraits the positive or negative trend of the correlation. A 55% correlation indicates a positively moderate correlation between the variables. Moreover, the lack of thorough understanding of the statistical terminology attributed to the incorrect

interpretation of the statistical results of regression outliers, nonlinear correlation, and coefficient of determination (r^2) as mentioned above.

In summary, Amelia established the skills of knowing what and how to investigate a statistical question regarding the topic of Regression Analysis. Amelia's greatest improvement in learning the course of introductory statistics reflected on her having data consciousness including being able to differentiate between qualitative data and quantitative data, and having consciousness of dealing with missing data in an appropriate way. Being able to communicate statistical results with people who are not familiar with statistics was another big achievement for Amelia in learning the course. Amelia progressed from interpreting the results without including the context to being able to use non-technical terms with the context. By the end of the course, Amelia was able to discuss the statistical results with comfort. However, she did not overcome the difficulties of correctly interpreting the statistical results. Her deficiencies in giving correct interpretation stemmed from incorrect statistical concepts due to the lack of thorough understanding of the statistical terminology.

Charlie.

1. Findings associated with statistical literacy
    a. Data consciousness

Data Type

Not being able to differentiate between qualitative data and quantitative data was found in Charlie's postings. One instance of confusion between the data types appeared at the time of learning

Regression Analysis. Students were asked to choose two quantitative variables of their own and conduct an analysis of the correlation between the two chosen quantitative variables. The two variables Charlie chose were the birth year of his *Facebook* friends and the number of wall posts. Although the variable of the number of wall posts was quantitative, the variable of birth year was not. Charlie mistook the seemingly quantitative display of the birth year (1993, for example) as a quantitative variable.

Another instance of negligence of differentiating between the data types occurred when learning Sampling & Inferences on Population Means. In his project, Charlie posted, "The quantitative variable I chose for this portion of the project is 'Age'." However, instead of estimating the mean age of his *Facebook* friends, Charlie stated, "Of the 280 individuals, my claim is that at least 75% of them are younger than 25." Apparently, Charlie was not aware that estimating proportion (75%) involved analyzing qualitative data of the 'yes' count to the survey question 'Are you younger than 25?' rather than analyzing the quantitative data of age.

Valid Data

In the beginning of the course, Charlie did not establish the consciousness of handling the missing data. This can be seen in his project for Descriptive Statistics when he chose to analyze the relationship status of his *Facebook* friends (Figure 7). Without excluding the missing data, Charlie concluded that the mode was "the category marked with the asterisk" where asterisk represents the missing data. Charlie translated the

mode of ‘asterisk’ as, “Typically, my friends chose not to display a relationship status.” Although true, it defeated the purpose of understanding the relationship status of his *Facebook* friends. More suitably, Charlie should confine his data analysis to those who entered the relationship status. Later in his project for Sampling & Inferences of Population Means, Charlie consciously avoided those who did not enter the information by “focusing on the 429 friends that did in fact like a number of pages” when he analyzed the number of likes of music pages of his *Facebook* friends.

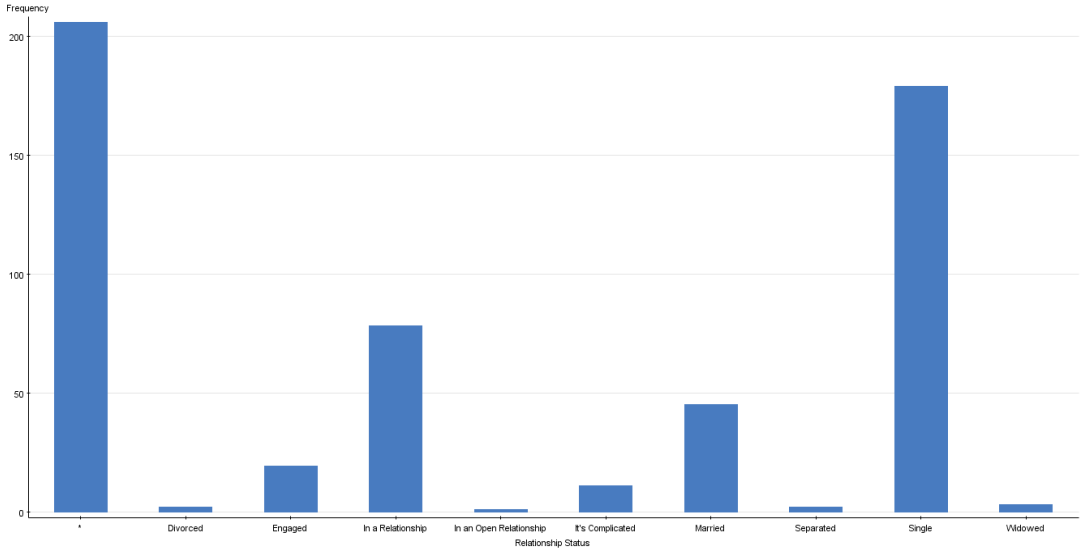


Figure7. Bar chart of the relationship status of Charlie’s *Facebook* friends

However, in handling missing relationship status of his *Facebook* friends when Charlie compared the difference of proportions of single status between his male and female *Facebook* friends, Charlie inappropriately assigned a failure to all his friends who were not single including those who did not report the relationship status. Assigning a

failure to a missing status was assuming the friend was not single, which may not be the case. The incorrect handling of the missing data produced inaccurate statistical results.

b. Understanding statistical concepts and terminology

Terminology

In learning the course topic of Descriptive Statistics, there were no major issues for Charlie in regard to the understanding of terminology. However, as the semester continued, new statistical terms were introduced with the new topics. It seemed that Charlie was overwhelmed by the large number of statistical terms. Many incomplete statistical concepts were detected in his postings due to the incomprehension of the terminology.

The misuse of the statistical terms related to statistical inferences appeared several times in Charlie's postings. For example, 'average' is used to replace the statistical term 'mean: "The parameter will be the average number of music likes amongst my friends." Charlie was confused constructing a confidence interval with conducting a hypothesis test. He used the term 'confidence interval test' as in this posting: "With these two factors, the sample results used above qualify 95% confidence interval test." The confusion between a sample mean distribution and a sample distribution was seen when Charlie incorrectly used sample statistics in describing the center and the variation of a sample mean distribution.

Perhaps the most confusing usage of the statistical terms for Charlie was the misusage between proportion and mean. Attributing to the lack of data consciousness, Charlie mistakenly termed the proportion as the mean. For example, in his weekly discussions where the word 'United' was found 12 times in his random selection of 1000 words from a text. Therefore, the sample proportion of having the word 'United' in his sample was 0.012. However, Charlie used the statistical term 'mean' to describe the numerical value of 0.012: "From 1000 words taken from the text, the mean was 0.012." This same mistake occurred again in his project discussions when he found the proportion of his female *Facebook* friends to be 0.516 but termed it as the mean.

The confusion between proportion and mean continued when Charlie discussed the center of the sample proportion distribution in his project. The center of a sample proportion distribution should be the population proportion. However, Charlie stated, "We use the mean to determine the center" when no mean could be found from qualitative responses. This confusion between proportion and mean contributed to the claim stated in his project that he wished to estimate "the number of friends that are female". The term "number of friends" was falsely stated and gave an impression of dealing with a quantitative variable when in fact the variable should be 'gender', a qualitative variable.

Statistical Concepts

In his weekly discussions, Charlie selected a random sample of 25 lectures from the entire *iTunes* library collection and constructed a histogram (Figure 8). Charlie's vague understanding of the statistical terms of center, variation, mean and standard deviation can be seen in his posting when he described the center and the variation of a symmetric distribution:

> *We follow the rules of a normal distribution. Such rules indicate that we would use the center to determine the mean. This mean/center is 85. This means that the average lecture is about 85 minutes long. The variation is given in the standard deviation, which is 23 minutes*.

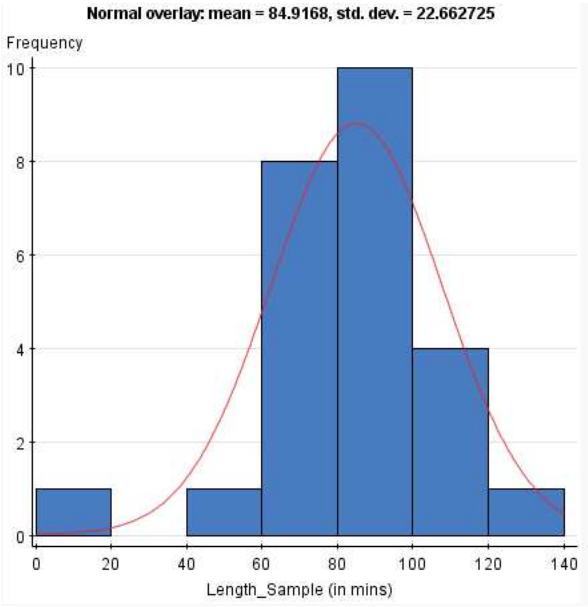


Figure 8. Histogram of Charlie's sample of lecture lengths

Continued with the same context, Charlie incorrectly described the sampling distribution of the sample mean (or, the sample mean

distribution) as follows: “The sampling distribution of the sample mean is 85.” Sampling distribution of the sample mean is a distribution of all the sample means of all the samples with the same sample size randomly selected from the population. It is a distribution describing the collection of sample means, not just one sample mean as described by Charlie. Putting in context, the sample mean distribution should be described as the distribution of the sample mean lengths of all the samples of 25 lectures randomly selected from the entire collection. Charlie continued to say, “This is in accordance to the Central Limit Theorem which states the population mean would be the same as the mean for the 25 lectures used in the sample.” The mean of 25 lectures selected in a sample is the sample mean. The sample mean, mostly likely, is not the same as the population mean. Rather, the mean of all the sample means collected in the sample mean distribution is, according to the Central Limit Theorem, the same as the population mean.

Charlie was confused with the two important probabilities involved in hypothesis testing, namely, level of significance and *p*-value. In testing the hypothesis that the mean lecture length of all the lectures in the collection to be longer than 80 minutes, Charlie wrongly interpreted the significance level as a probability of null hypothesis being true. Rather, the significance level should be the probability of rejecting the null hypothesis when in fact the null hypothesis is true. With the inclusion of confusing technical terms and an incorrect interpretation, Charlie

incorrectly explained the meaning of using a significant level at 5% as, "The probability of making a false inference based on the random sample we obtained which was a mean lecture length greater than 80, is only 5%."

Similar to the level of significance, the *p*-value shows the probability of making a Type I error based on the sample evidence. The smaller the *p*-value is, the less probability of making a Type I error according to the sample evidence. Hence, the smaller the *p*-value is, the stronger the evidence to reject the null hypothesis. The value of the *p*-value should not be used to judge the truth-value of the null hypothesis. However, Charlie showed his incorrect conceptual understanding of the *p*-value when commenting, "The smaller the *p*-value, the more likely it is that the null hypothesis is false." This exact same wording showing the misconception of the *p*-value was posted again weeks later in his weekly discussions when testing a population proportion.

c. Interpreting statistical results using non-technical and layman's terms with context

Context

Charlie failed to include the context when making an interpretation of the statistical results. For instance, "The variation of the sample is shown by the standard deviation which is 22", and "The confidence interval (17.40, 27.71) means that we can conclude with a 95% level of confidence that the mean is between these two numbers."

Non-technical Terms

In hypothesis testing, the interpretation of a Type I error and Type II error using non-technical terms was especially challenging for Charlie. Although Charlie understood that a Type I error would be made "if I said the null hypothesis was false when in fact it was true", the interpretation made in his weekly discussions was unclear and incomplete: "if I said of the Muslims [in the] surveyed [27 countries], there was not exactly 50% who believed the story to be untrue." In the project, the interpretation Charlie made on a Type I error and Type II error regarding his *Facebook* friends residing in California was again incomprehensible and confusing.

> *Type I error would have been if I would have rejected the null hypothesis stating that 55% of my friends resided in California when there was significant evidence to prove otherwise. If I would have failed to reject this hypothesis of 55% of my friends residing in California and there was not significant evidence to prove my hypothesis, I would have made a Type II error.*

2. Findings associated with statistical reasoning
    a. Understanding statistical processes

Hypothesis Test

In discussing the hypothesis testing on a claim that the mean lecture length of all the lectures collected in the researcher's *YouTube* library collection to be longer than 80 minutes, Charlie's comments on the

hypotheses revealed his incorrect conceptual understanding of the process of hypothesis testing.

> *The null hypothesis is only an estimate so expect this to be wrong. We would like to keep this estimate only moderately wrong. This means it should more accurate than not. The alternative hypothesis is more general. It deals with greater than and/or less than which allows for a broader range of accuracy.*

When making inferences of population proportions, Charlie still struggled with the incomprehensive understanding of the hypothesis testing process. He posted in his weekly discussions, “As stated in the module, we would first assume the null hypothesis to be true which states that exactly 50% of the Muslims [in the] surveyed [27 countries] believed the story to be untrue.” To be able to reject the null hypothesis, one needed to have significant sample evidence. Without giving the explanation why the sample evidence was significant, Charlie wrote, “I do believe the evidence to be statistically significant. There is no indication of otherwise.” On the other hand, having significant sample evidence does not justify the eligibility of making inferences to the population. Rather, inferences can only be made when the sample statistic was obtained from a representative sample. However, Charlie went on to say, “We would use the sample evidence to make inferences that apply to the whole population” without addressing the issue of the sample being representative.

Charlie's project discussions on the hypothesis testing showed a serious flaw of his understanding the process. The statistical concept of testing a population parameter is to use a sample statistic as the evidence and conclude about the hypothetical parameter without having the knowledge of the parameter. In the project, Charlie tested the hypothesis of having majority of his *Facebook* friends claiming California as their hometown state. He began by finding the proportion (55%) of all of his *Facebook* friends who claimed California as their hometown state. With the known population proportion of 55%, Charlie tested that the population proportion of his *Facebook* friends who claimed California as their hometown state to be 55%. Sure enough, the testing result was that 55% of his *Facebook* friends were from California.

In preparing and getting ready to conduct a hypothesis test, much statistical concept is involved in making the choice of level of significance, checking the satisfaction of the requirements for testing, and making the choice of a test statistic. Charlie's misconceptions on these issues were revealed in his postings.

Level of Significance

Choosing an appropriate significance level is to safeguard the minimal tolerance of committing a Type I error. There was no 'accurate' level of significance as claimed in Charlie's weekly discussions: "The significance level I would use would be 5%. I chose to use this because it is usually an accurate alpha to use when conducting a hypothesis test."

Normality Assumption

The requirement of the normality assumption for inferring the population mean is to ensure the eligibility of converting the sample statistic into a standardized *z* score or *t* score. However, Charlie reversed the cause and the consequence: “The normality assumption aspect is satisfied by the fact that the sample uses a *z*-score which means it has a normal distribution.” Later for constructing a confidence interval to compare the difference of proportions of single status between his male and female *Facebook* friends, Charlie failed to check the minimum requirements of at least 10 successes (having a single status) and at least 10 failures (not having a single status) to satisfy part of the normality requirements. Of Charlie’s samples of 25 male and female *Facebook* friends, only 9 were non-single in the male sample and only 8 were single in his female sample. The confidence interval constructed was considered invalid due to the failure of meeting the minimum success and failure requirements.

Test Statistic

The choice of a test statistic for inferring a population mean depends on the availability of the population standard deviation. A *t* test statistic should be used in replacement of the *z* test statistic when testing a population mean with an unknown population standard deviation. Charlie made an incorrect choice of a *z* test statistic in his weekly discussions. However, the justification of using a *z* score was because “we are dealing

with a sample". This incorrect choice continued in his project discussions. Charlie constructed a *z* confidence interval instead of a *t* confidence interval when the population standard deviation was not available. Similarly, the incorrect choice of a *z* test over a *t* test occurred for testing the mean age of his *Facebook* friends and testing the difference of mean number of viewers between two *YouTube* channels under the situations where the population standard deviations were not available.

b. Being able to interpret statistical results

Descriptive Statistics

In regard to the course material of Descriptive Statistics, Charlie was not sure how to describe the distribution of the number of photos tagged to *Facebook* pages from a histogram (Figure 3). Without the context, Charlie posted,

> *The graph is skewed to the right. This indicates that the number of photos that have this page tagged is most frequent from 0-500 and declines from this point on. The graph has 1 mound, which shows that the sub group of 0-500 is larger than the rest of the sub groups.*

With the majority of the *Facebook* pages surveyed having up to 500 photos tagged, the one having more than 4000 photos tagged to the page should be considered as unusual. However, Charlie concluded, "There are no unusual values because no values are unusually low or unusually high."

Regression Analysis

In learning Regression Analysis, Charlie discussed the trend between the number of hours worked per week and the number of credit hours taken from a scatterplot (Figure 6). While the scatterplot clearly showed a linear trend, Charlie concluded with a nonexistence of linear trend. One possible explanation for Charlie not considering the trend as linear might come from a wrong understanding that all the observations have to be tightly close to a line to be considered as linear.

The coefficient of determination (r^2) between the work hours and the number of credit hours taken was found to be 72%, which indicated that 72% of the variation in the number of credit hours taken can be explained by the work hours through the regression model. However, Charlie's posting in regard to the interpretation of the coefficient of determination (r^2) was incomplete: "Based on the linear regression model, roughly 72% of the variation can be explained." Furthermore, there was no mentioning in Charlie's posting that with an r^2 of 72%, the model provided a good prediction of the number of credit hours taken through the work hours.

Inferential Statistics

The concept of 'proving' the hypothesized parameter to be 'true' or 'false' through the results of a hypothesis test or a confidence interval was incorrectly and repeatedly brought up by Charlie when learning the topics of Sampling & Inferences for Population Means and Sampling & Inferences for Population Proportions. Hypothesis testing involves using

sample evidence to reject or not to reject the hypothesized parameter. Since the parameter is unknown, rejecting the hypothesized parameter does not imply that it is a false hypothesized parameter. Likewise, failing to reject the hypothesized parameter does not imply that it is a true hypothesized parameter. Therefore, hypothesis testing cannot be used as a proof process to conclude which hypothesis is true or false. In comparing the difference between the mean numbers of views from two *YouTube* channels when Charlie concluded, “There is significant evidence to prove that there is a difference between the two means.”

The incorrect statistical concept of ‘proving’ one hypothesis being ‘true’ or ‘false’ appeared in learning the course topic of Sampling & Inferences of Population Proportions. With a *p*-value of less than 0.0001, one rejects the null hypothesis. In context, this would be interpreted as more than 50% of the Muslims in the surveyed 27 countries considered the story of killing Osama bin Laden was untrue. However, Charlie concluded, “The null hypothesis is false in this case.”

Similarly, the truth-value of a parameter could not be confirmed through the results of a confidence interval either. When Charlie discussed the 95% confidence interval constructed for estimating the mean age of his *Facebook* friends, he falsely confirmed that the sample mean age (22.55) was the mean age of all his *Facebook* friends: “This means that we can say with 95% level of confidence that the population mean is 22.55 based on the results taken from the sample.”

In the weekly discussions on the topic of hypothesis testing on the mean lecture length of all the lectures collected in researcher's *YouTube* library, Charlie incorrectly applied the rule of rejection and concluded with an incorrect conclusion. The hypothesis test produced a *p*-value of 5.67%, which was higher than the significance level of 5%. With this result, one should not reject the null hypothesis since the *p*-value was greater than the significance level. However, Charlie decided to reject the null hypothesis because "My *p*-value was slightly over 5%. My interpretation of this is that the null hypothesis is significantly false." Charlie seemed to mistakenly consider the *p*-value as the probability of the null hypothesis being false. He continued to state, "Even though the *p*-value is not exactly what we would say to be false, it is rather close to what we would call false." In concluding the test results, Charlie rejected the mean lecture length of all the lectures in the collection being 80 minutes long (as stated in the null hypothesis), but concluded that the sample mean (89.04) should be the population mean, "The null hypothesis stated $\mu = 80$ when actually $\mu = 89.04$."

The same mistake was made in Charlie's project discussions when testing the mean age of his *Facebook* friends being younger than 25 years. Charlie made the test decision subjectively according to his own wish rather than following the objective rule of rejection.

The null hypothesis states that the average age of my friends would be equal to 25. I would disagree in this case. I would much rather go

with the alternative hypothesis which states that the mean age of my friends would be less than 25. This better suits my claim that at least 75% of my friends are younger than 25.

Another incorrect concept about the *p*-value appeared when comparing the mean recitation times between the two reciters. With a significance level of 5% and a *p*-value found to be 12.03%, Charlie stated, "In this case it would be more than likely that the null hypothesis is false because the 12.03% is rather close but to be on the safe side I wouldn't reject the null hypothesis. The alternative hypothesis held to be true." A large *p*-value suggests an insignificant sample evidence to reject the null hypothesis. The magnitude of the *p*-value (large or small) should not be used as an indication of true or false null hypothesis.

When explaining if one can conclude a plausible difference of number of views between the two *YouTube* channels from a significant hypothesis test result, Charlie stated, "There appears to a difference between the two channels but it is hard to tell because the sample size and standard deviations are different." Hypothesis test results provide a test statistic and a *p*-value. It does not provide a plausible interval of differences between the two compared groups. The population means of two independent groups can be compared using a two-sample *t*-test under certain conditions with different sample sizes and sample standard deviations. Therefore, sample sizes and standard deviations were irrelevant to the question.

The misinterpretation of the results was also found when Charlie interpreted the confidence interval constructed for comparing the proportion of males and females having experiences with marijuana. The confidence interval of the difference between two proportions was found to be $(5\%, 11\%)$, which indicated that the percentage of male 12^{th} graders having experiences with marijuana was about 5% to 11% higher than the percentage of female 12^{th} graders having experiences with marijuana. Charlie, however, incorrectly interpreted the interval result of $(5\%, 11\%)$ as, "There is a difference in the proportion of males and females who use Marijuana. We can say with a 99% level of confidence that the difference between the two proportions is between 0.05 and 0.11."

Charlie was confused by the statistical analyses of comparison between two groups and with finding the association between two variables. He constructed a confidence interval to compare the difference of proportions of single status between his male and female *Facebook* friends. However, Charlie posted, "I want to know if the fact that an observation is male has any relation to a single status." Because of the misunderstanding, Charlie interpreted his confidence interval result of $(-3\%, 51\%)$ as an indication of "being a male does make it more likely to be single."

3. Findings associated with open-ended interview and summary

Charlie's interview question was related to making inferences of population means, particularly, comparing the difference of two means from

dependent samples (Appendix K). The process could be accomplished through either conducting a hypothesis test or constructing a confidence interval. Charlie's reply to the first part of the interview revealed his incompetency in statistical thinking. The capability of viewing the entire statistical process as a whole was not established through the learning of the course.

> *In this case I would use a 95% interval test to determine whether or not male daters overstate their height in online dating profiles. The success in this study would be yes the observation did overstate their height and failure in this case would be if they put their actual height, understated their height or did not list any height. One would have to determine the actual height of the observations in the sample and compare such results with the heights listed on the sites. The sample would have to be chosen at random and the sample would have to fit the qualifications of the normality assumption. To fit the normality assumption, the population would have to be 10 times the sample size and the sample would have to be large enough to have 10 successes and 10 failures. I chose this test because it would give an unbiased estimation of the proportion of males who did overstate their heights on their online profile. Such a test would allow for inferences to be made on the entire population thus making it possible to say if the majority of males overstated their height or not.*

In the follow-up prompt, Charlie was asked to elaborate on the following specific questions: Why would you prefer a confidence interval to a hypothesis test? Are there any particular reasons of your choice? Also, please be specific

about the statistical analysis method you prefer, for instance, confidence interval of what (parameter)?

Charlie's responses to the follow-up questions were recorded below:

As I was reading my statement I wanted to change it but I remembered you said once submitted we could not change it. I actually think a hypothesis test would be more appropriate. I say this because I used majority. My would be Ho =.50 and my null hypothesis would be >.50. I say this because anything over .50 would be considered majority. I believe the population parameter would be the Sampling Distribution of the Sample Mean.

Charlie's replies to the second part of the interview questions reflected his shortages of statistical reasoning capabilities. Charlie did not understand the statistical process given in the scenario. In addition, he failed to interpret the statistical results correctly.

No there is not significant evidence that on average male online daters overstate their height in online dating profiles. The confidence interval states that the sample mean is between .31 and .83. The sample mean height even differs from the actual mean by .57 and the standard deviation in height is .81. These proportions are too large to make any inferences on the population.

No he cannot generalize his conclusion [to all the online male daters]. Once again, his confidence interval has too large of a margin to make any generalization. The interval is (.31, .83). If the sample mean falls at .32

then it would mean the majority of males don't overstate their height and if the sample mean was .82 that would mean that the majority did overstate their height.

In summary, Charlie struggled with interpreting statistical results correctly throughout the semester. Charlie showed fragmented conceptual understanding of the statistical processes of making inferences of the population means and making inferences of the population proportions through conducting a hypothesis test or constructing a confidence interval. In addition to the lack of reasoning and thinking statistically, the interview results revealed Charlie's lack of fundamental understanding in the area of statistical literacy. Specifically, Charlie showed no data consciousness when applying statistical analysis to the data collected. Attention was not given to the data type prior to the data analysis, which resulted in the uncertainty of inferring between means and proportions. Incorrect and incomplete statistical terms were found when responding to the interview questions. Solid understanding of the statistical terms ensures sound statistical concepts. Charlie's overall performance for the entire course period was insufficient conceptual understanding in terms of statistical literacy, reasoning, and thinking.

Harry.

1. Findings associated with statistical literacy
    a. Data consciousness

Data Type

Harry displayed his consciousness of data type of a variable being qualitative or quantitative throughout the entire study period. For example, in his weekly discussions when learning Descriptive Statistics, he posted "Since the variable of Popular Week is qualitative, the typical outcome should be determined by the mode."

Valid Data

In the beginning of the semester, Harry handled missing data incorrectly. When analyzing the relationship status of his *Facebook* friends, Harry included those who declined revealing their relationship status in his analysis. Instead of concluding that typically, his *Facebook* friends were single (after excluding the missing data), Harry concluded by posting the following:

> *From my bar chart, I conclude that the relationship status with the highest occurring frequency among my friends is actually '*', which means they have declined to list a relationship status … Therefore, the center, or typical value of this data set, is * (declined to list).*

Proper handling of the misinformed data is another aspect of having consciousness of including the relevant data. When incorrect data are detected, the statistician should take precaution of either correcting or removing the data. The inappropriate handling of the misinformed age provided by his *Facebook* friends was found in Harry's project for Descriptive Statistics. Harry explained how he handled the inaccurate data when one of his *Facebook* friends reported an age of 107: "The *Facebook*

friend … is my friend [named removed], who was mostly likely attempting a poor joke when he entered his age into *Facebook*, since I know for a fact that he is 20 years old. However, as it pertains to our data, his age is 107."

Harry's handling of the irrelevant data was corrected and appropriately addressed for the remaining of the semester. In learning Sampling & Inferences on Population Means, Harry excluded the missing data as stated in his posting, "For this first part of the project, I have chosen to estimate the population mean number of movie likes between all my friends on *Facebook* that entered a value under the '# of movie likes' column." When learning Sampling & Inferences on Population Proportions, Harry compared the proportions of his *Facebook* friends having single status between male and female friends. He excluded those data without specifying the relationship status prior to his random selection of samples from his male and female *Facebook* friends.

b. Understanding statistical concepts and terminology

Terminology

The confusion between similar statistical terms was found in learning Regression Analysis. For instance, Harry used correlation to explain coefficient of determination (r^2) of 72%: "The data shows that the *r*-squared value reveals a 72% correlation. This is a high correlation rating!" Another instance of confusion between similar terms was found when Harry interpreted the coefficient of determination: "We understand

this to mean that a full 72% of the variance in the number of credit hours can be explained by the above model." Note that Harry was confused between the terms variation and variance. Variation and variance are two different statistical terms even though they have similar meaning. Variation refers to the variability while a variance is a numerical value of the square of a standard deviation.

The misusage of statistical terminology was also found in Harry's weekly discussions on the topic of sample mean distribution. Sampling distribution of the sample mean is also known as sample mean distribution. Harry incorrectly used "sampling distribution of the population mean" for the term *sampling distribution of the sample mean*, and "sample distribution mean" for the term *sample mean distribution*.

Statistical concepts

Harry was able to describe the sample distribution in terms of its shape, center, and variation when learning the topic of Descriptive Statistics. Specifically, Harry demonstrated the correct understanding of the center of a data set: "Center is described as a typical value of a data set". However, Harry incorrectly described the number of mounds appeared in the graphical display of a histogram constructed for analyzing the age of his *Facebook* friends in his project discussions (Figure 9). Statistically, a mound should be determined by a clear separation of bars, not by the 'size' of the bars alone as cited in his posting:

There is one major mound appearing in the distribution of 'Age', suggesting that the frequency of one particular subgroup (between 20-40) is higher than the rest of the subgroups in the distribution.… Of note, however, is the smaller spike from the 0-20 'Age' subgroup. However, this is not large enough to be considered a true mound.

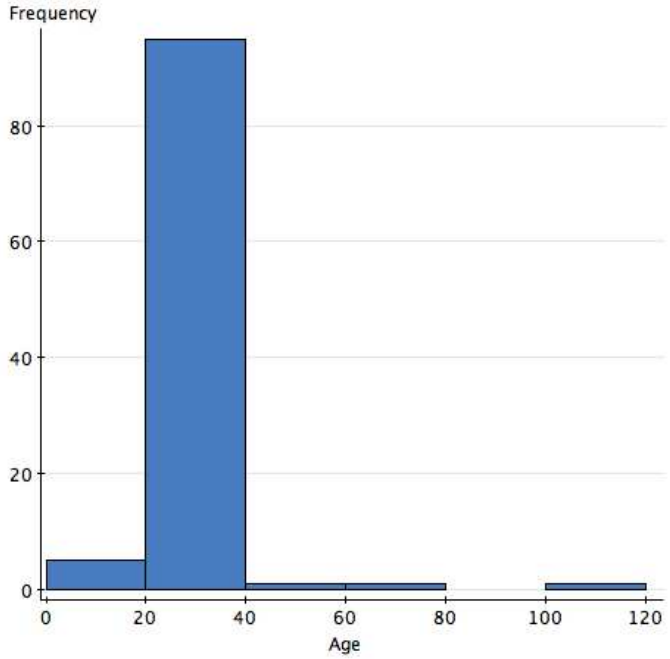


Figure 9. Histogram of the age of Harry's *Facebook* friends

When sample distribution was reviewed later prior to the learning of Sampling distribution, Harry incorrectly described the shape of the histogram due to his incorrect naming the direction of the skew following the mound. "The histogram above shows a heavily skewed shape, specifically to the left." Harry correctly described the center and the variation of the distribution. Specifically, the sample standard deviation was correctly interpreted, "The standard deviation is 27.33, which tells us

that the lengths (in minutes) of each lecture contained in my sample deviates from the sample mean by roughly 27.33 minutes."

Standard error of a sampling distribution is much similar to the standard deviation of a sample distribution. Although Harry understood that the standard deviation of a sample described a typical deviation of individual observation from the sample mean, he failed to comprehend that the standard error of the sample mean distribution described a typical deviation of the sample mean from the population mean. "We find the standard error to be 5.154 minutes. This means that, accounting for all the different possible combinations of 25 objects (which form a sample), taken from the population of 59, the mean values of all the samples would deviate by about 5 minutes."

However, as the learning continued, Harry demonstrated a clear understanding of the standard error of a sample proportion distribution. A correct statistical concept of defining the sample proportion distribution was also found in the weekly discussions when students were asked to choose a document from a given website and define a word of their choice as a success (picking a particular word 'the' as a success, for example). Using the success defined, Harry flawlessly described the corresponding sample proportion distribution as, "The sampling distribution of the sample proportion of 'the' words of a sample size of 500 is the distribution of all the sample proportions of 'the' words calculated from all the

samples of 500 words randomly selected with replacement from the transcript of the Emancipation Proclamation."

Harry's clear conceptual understanding of the precision of an estimator was demonstrated when he discussed the variation of the sample proportion distribution. With a standard error of 0.00053, Harry contributed the small standard error (variation) to a large sample size. He commented on the precision of the estimator produced from a large sample that is used to estimate the parameter, "The large sample size of 500 words helps to create a tiny standard error of less than half a percent, which indicates the high precision of targeting the population proportion using the sample proportion produced from a sample of 500 words."

However, Harry was confused between the sample distribution and the sample proportion distribution. Hence, in response to the description of the shape of the sample proportion distribution when estimating the proportion of his single *Facebook* friends, Harry claimed that it was not possible to describe the shape of the distribution of a qualitative data set. Although Harry's claim was true for qualitative data, the sample proportion distribution describes the distribution of all the sample proportions (numerical data) of single relationship status on his *Facebook* list. Therefore, unlike what Harry claimed, it was suitable to discuss the shape of the sample proportion distribution.

In response to the choice of confidence level, Harry chose to use 99% instead of 95%. His justification of using a higher confidence level

leading to a higher level of accuracy was an incorrect statistical concept. Rather, a higher confidence level ensures a higher reliability in terms of the estimation results.

> *I'm choosing to set my confidence level at 99%, due in part to the very large sample size. This will make the confidence interval technically less precise, but not by much, while also having the added benefit of making it much more accurate than, say, a 95% confidence interval*.

On the other hand, an accurate translation of the level of significance was found in his weekly discussions: "Using 5% as a significance level means that the probability of making a false conclusion that the mean lecture length of all the lectures collected in Ms. Miao's *iTunes* library is longer than 80 minutes while in fact it is not is maintained at no more than 5%."

c. Interpreting statistical results using non-technical and layman's terms with context

Context

With a correct understanding of the statistical terms Type I error and Type II error, Harry interpreted the terms without including the context. "If I were to analyze the sample data and find the population mean to be greater than 80, when in fact the population mean is equal to 80" and "If I were to analyze the sample data and find the population mean to be 80,

when in fact the population mean is greater than 80", for Type I error and Type II error, respectively.

In describing the population distribution as the distribution of all the words appeared in the transcript of the Emancipation Proclamation, Harry failed to give a precise description of the population distribution in context. "The population distribution in this context is a binomial distribution with a success defined as selecting the word 'the'."

Non-technical Terms

Being able to communicate in layman's terms when explaining the statistical results was a challenge to Harry in the beginning of the semester when learning Descriptive Statistics. The challenges can be seen in the following posting as shown in the weekly discussions. "The week when the most people were talking about this page (popular week) is 07/15/12, which reached a graph-high 7 frequencies. The next most-frequent week was 12/16/12, with 6 frequencies", and

> *The distribution of 'photos' is skewed to the right, which suggests to me that the majority of the number of 'photos' is at the lower end (between 0-500) with very few Facebook pages having a value for 'photos' greater than 4000.*

Although Harry struggled with interpretation in clear context in weekly discussions, the following postings in his topical project showed statistical interpretations of center and variability, respectively, in clear context with non-technical terms. "That is, the typical age of a given

friend of mine on *Facebook* is 22", and "The IQR for this data set is 3. This means that the middle 50% of my friends on *Facebook* that listed an age vary by as much as 3 years."

Harry interpreted the slope of the regression model between work hours and credit hours taken clearly in layman's term with context as follows, "The data shows that for students who work, each time there is an increase of one hour spent at work, there is a decrease of roughly half of a credit hour taken (.445632) that follows."

When interpreting the *p*-value, Harry failed to address it in non-technical terms as the probability of concluding that the mean lecture length is longer than 80 minutes when it is in fact 80 minutes. Rather, it was interpreted as the following: "The probability of rejecting that the mean lecture length is 80 minutes (the null hypothesis) when it is in fact 80 minutes, is less than 2%."

2. Findings associated with statistical reasoning
    a. Understanding statistical processes

Randomization and Normality Assumptions

The process of making inferences of a population parameter (mean or proportion) requires the fulfillment of randomization and normality assumptions. Harry demonstrated a clear understanding of the purpose of randomization requirement was to be able to "infer the confidence interval results to the entire population of lectures contained in Ms. Miao's *iTunes* library." As for the normality assumption, it refers to the normal

distribution of the sample mean distribution not the sample distribution as stated in Harry's posting: "The sample must follow a relatively normal distribution, which is referred to as the normality assumption." However, later in his project, Harry described precisely and clearly in regard to the normality assumption.

> *We need to make sure that the sample mean distribution does follow a normal distribution. Central Limit Theorem states that as long as the population distribution is a normal distribution, then the sample mean distribution is a normal distribution. If the population distribution is not a normal distribution (as is the case with our population) then the sample size needs to be large enough (usually at least 25) for the sample mean distribution resembling a normal distribution. Since we have already selected a sample size that satisfies this requirement, we can consider it qualified.*

Hypothesis Testing

The process of hypothesis testing involves the rejection of the presumption of a true null hypothesis and concluding the support of the alternative hypothesis through significant sample evidence. Harry's posting in his weekly discussions demonstrated his understanding:

> *For the purpose of hypothesis testing, the null hypothesis is assumed to be true. In this case, we assume the statement 'the population mean lecture length is 80 minutes' is true. The alternative hypothesis represents a statement that we are trying to find evidence to support.*

In this case, we are trying to find evidence to support the hypothesis that ‘ the population mean lecture length is greater than 80 minutes’.

The posting of Harry’s project for testing population means in relation to a hypothesis test showed a complete hypothesis testing procedure with clear understanding of the statistical concepts. Harry began the process by choosing the variable of age and defining the population. “The population that I will be sampling from contains each of my 302 Facebook friends that entered a value under the ‘age’ column.” Harry understood a hypothesis testing is to make decision on the presumed hypothesized population parameter based on the sample evidence (sample estimator).

I begin with the assumption that the population mean age is 20 years. Next, I’ll use the sample mean of 22.63 years as evidence in a hope to reach a decision that we could reject the presumption. If that happens, we say that the sample mean is significant to conclude that the population mean age is older than 20 years. Alternatively, if we fail to reject that the presumption is true, and then we say that the sample evidence is insignificant to conclude that the population mean age is older than 20 years. We will use the sample mean as evidence in testing the claim of a population mean, due to the fact that the sample mean is what’s known as an unbiased estimator to the population mean.

Harry then discussed the selection of level of significance in context.

Next, we must select a significance level for the hypothesis test. The significance level is the probability of rejecting H_0 when H_0 is true, also known as making a Type I error. The significance level is prescribed prior to conducting the test in order to keep the probability of making such a mistake as low as possible without compromising the quality of the test. This can usually be achieved at a = 5%. Putting this in context, a significance level at 5% means that the probability of making a false conclusion that the mean age of all my friends on Facebook is older than 20 years while in fact it is not is maintained at no more than 5%.

Next, a justification of using *t*-test instead of a *Z*-test was given:

Also, before we are ready to go forward with this hypothesis test, we must choose an appropriate test statistic. To choose an appropriate test statistic means that we need to choose the correct sample estimator, which is to say, an unbiased estimator, and its sampling distribution. Typically, when testing the population mean, the sample estimator is the sample mean and the sampling distribution of the sample mean is a Z distribution. In our case, since the population standard deviation can be easily found out using StatCrunch, we can use Z distribution. However, for the purposes of this project, I will assume that the population standard deviation is unknown. Therefore, there is a need to use sample standard deviation to estimate the population standard deviation when calculating the

standard error. Because of this, a modified t-distribution would be used instead of the Z distribution.

The next paragraph in Harry's posting showed his clear understanding of the relationship between the computed *p*-value and the prescribed level of significance.

P-value is similar to significance level in that they are both probabilities of making a Type I error. The major difference is that the significance level is a probability prescribed before the hypothesis test is actually performed. P-value, on the other hand, is the actual probability of making a Type I error computed from the sample estimator. We use significance level as a guideline to decide if we could reject the null hypothesis by comparing it with the p-value. So long as the probability of making Type I error computed from the sample evidence (P-value) is less than or equal to the prescribed probability of making a Type I error (significance level), we feel safe to reject the null hypothesis. On the other hand, if p-value had been larger than my level of significance, I would have felt that the chance of making Type I error was too high, and I would have avoided rejecting the null hypothesis. This, however, puts me at risk of making Type II error, which would mean rejecting my alternate hypothesis of $\mu > 60$*, when in fact this is true.*

As the course continued, the discussion on the topic of testing on population proportion was fluently elaborated. Harry demonstrated clear

understanding of hypothesis testing especially in describing the null hypothesis, alternative hypothesis, Type I error, Type II error, significance level, and *p*-value in context. Continued onto the project, Harry did a complete and correct analysis on testing his hypothesis of having more than 50% female *Facebook* friends.

b. Being able to interpret statistical results

Descriptive Statistics

From a skewed distribution result, the center and the variation should be described by the median and the interquartile range (IQR), respectively. However, Harry incorrectly described the center and the variation using mean and standard deviation, respectively. “The center of the sample distribution is the mean number of movie likes of 21.4 and the variation of the sample distribution is the standard deviation of the number of movie likes of 36.43.”

Inferential Statistics

In interpreting a confidence interval result for the purpose of estimating the population mean, Harry gave correct interpretation in non-technical terms with the context: “With 95% confidence we can conclude that the mean lecture length of all the lectures given by Shaykh Riyadh collected in Ms. Miao’s iTunes library is between 79.14 minutes and 101.7 minutes, from about 1 hour 20 minutes to 1 hour 42 minutes long.”

However, Harry had difficulties interpreting the confidence interval result for the purpose of comparing the difference of two population

means. In his project, a confidence interval of $(-5, 2.5)$ was produced for the age difference between his female and male *Facebook* friends. The opposite signs of the end points of the interval indicated an insignificant sample evidence to conclude that there was a difference in age between the female and male *Facebook* friends due to the possibility of the mean age difference being zero. Contrary to the insignificant result, Harry interpreted the confidence interval result as "there is a statistically significant result that the difference in mean age in years between male and female *Facebook* friends of mine is between either of these options: men are, on average, 5 years older, or women, on average, are about 2.5 years older" due to "not much difference at all between the mean ages of my male and female *Facebook* friends".

This misinterpretation of the confidence interval results was corrected when Harry compared the difference of proportions of having single status between his *Facebook* male and female friends. With a confidence interval result of $(-0.15, 0.35)$, Harry concluded, "there is no statistically significant result that the proportion of my male *Facebook* friends that are single is different from the proportion of my female *Facebook* friends that are single."

3. Findings associated with open-ended interview & summary

The interview question Harry received at the end of the semester was about comparing the difference of two population proportions (Appendix L).

The statistical process of investigating if there is any difference between the two population proportions could be accomplished through either conducting a hypothesis test or constructing a confidence interval. The following response from Harry's first part of the interview reflected that he was able to view the entire statistical process as a whole. However, there were some deficiencies in his response in terms of what and how to investigate. Although Harry mentioned the word "comparing", he failed to identify what to compare specifically. That is, there was no specific mentioning of the parameters (population proportions) found in his reply. As for the process of investigation, Harry considered the process of conducting a hypothesis test was superior to the process of constructing a confidence interval. However, both conducting a hypothesis test and constructing a confidence interval were equally qualified to answer the question described in the scenario.

> *The question given to me has a clear, definitive question that we are trying to have answered. There is not simply a command to describe, or estimate a value for a population parameter. Instead, we are clearly asked to "determine if subjects with pre-existing cardiovascular symptoms were at an increased risk of cardiovascular events while taking subitramine, an appetite suppressant, comparing with those who took placebo." The important word in this sentence is "comparing". This suggests to me that the most appropriate course of action for the researcher to take is to conduct a hypothesis test.*

I can already see, based on this question, what the null and alternative hypotheses would be. The alternative hypothesis, or the hypothesis which we are testing, is to see if the subjects who took the appetite suppressant are at in INCREASED risk of cardiovascular events, as opposed to the placebo group.

The second part of the interview contained two questions. The second part of the interview evaluated the ability of statistical reasoning: understanding statistical processes and being able to interpret statistical results. Harry's response to the first question of this part of the interview revealed his understanding of the statistical process presented to him in the scenario. Although Harry was able to interpret the statistical results, the statistical concepts on level of significance and *p*-value were not well established.

By setting the significance level at 5%, we have pre-specified the likelihood that we will make a Type I error. A Type I error occurs when you reject the null hypothesis, even though the null hypothesis is true. A Type I error, in context, would be if we were to conclude that subjects with preexisting cardiovascular symptoms who take subitramine are at increased risk of cardiovascular events while taking the drug, when in fact there is no difference in risk between those that take the drug, and those that take a placebo. However, by examining our P-value (and armed with the knowledge that we set our significance level at 5%) we can feel comfortable knowing that it's unlikely that we will commit a Type I error. Our P-value, which is calculated at 0.022, or 2.2%, is lower than our

significance level, which means that we feel safe rejecting the null hypothesis. That being said, it's difficult to CONCLUDE anything from 1 study. Based on our hypothesis test results, however, using this sample we would say that there is statistically significant evidence that subjects with preexisting cardiovascular symptoms who take subitramine are at increased risk of cardiovascular events while taking the drug.

The conclusion Harry made in regard to the second question of the second part of the interview was incorrect. The causal effect could be established if data were collected from a randomized experiment.

I can't CONCLUDE anything about the greater population of patients with preexisting cardiovascular symptoms. This is only one study, and although there is statistically significant evidence, there is still a chance (indicated by the probability, or P-value) that we have committed a Type I error. Additionally, could be variables that the researchers failed to take into account. For example, the study samples 9804 people who were already overweight or obese, with preexisting cardiovascular disease and/or type 2 diabetes; these patients are already at increased risk of the primary outcome measured, and due to this fact, you can not conclude that subitramine CAUSES a greater risk.

In summary, Harry had no major issues of understanding the statistical processes and interpreting the statistical results throughout the entire semester. Although incorrect conceptual understanding of certain terminology led to incorrect interpretation of some of the statistical results, Harry showed his

capability of identifying relevant statistical results obtained from *StatCrunch* when analyzing the data. In the beginning of the semester, communicating the results in non-technical terms was found challenging for Harry. However, he overcame this issue as the learning progressed. Harry's good interpretation skill of using non-technical terms with context was also demonstrated in his interview replies. However, the skill of having consciousness of data type preceding the data analysis was not exhibited in the interview even though it was always well established in his weekly and project discussions. Despite some minor deficiencies in statistical literacy, Harry demonstrated very well capabilities in reasoning and thinking statistically.

Jessica.

1. Findings associated with statistical literacy
    a. Data consciousness

Valid Data

In the first part of her project for Descriptive Statistics, Jessica chose to analyze the qualitative variable Relationship Status of her *Facebook* friends. In describing the center of the relationship status from a bar chart (Figure 10), Jessica posted:

> *The center, or mode, of the bar graph is the answer with the most occurrences, and in this case "no answer" is the center. This means that over 200 friends decided not to fill out or answer the relationship status section of their Facebook pages.*

Jessica correctly used mode as the center for qualitative data. However, the issue of valid responses arises. For the purpose of understanding the relationship status of her *Facebook* friends, missing values were not relevant in understanding toward the relationship status. Therefore, the missing values should be excluded prior to performing the statistical analysis.

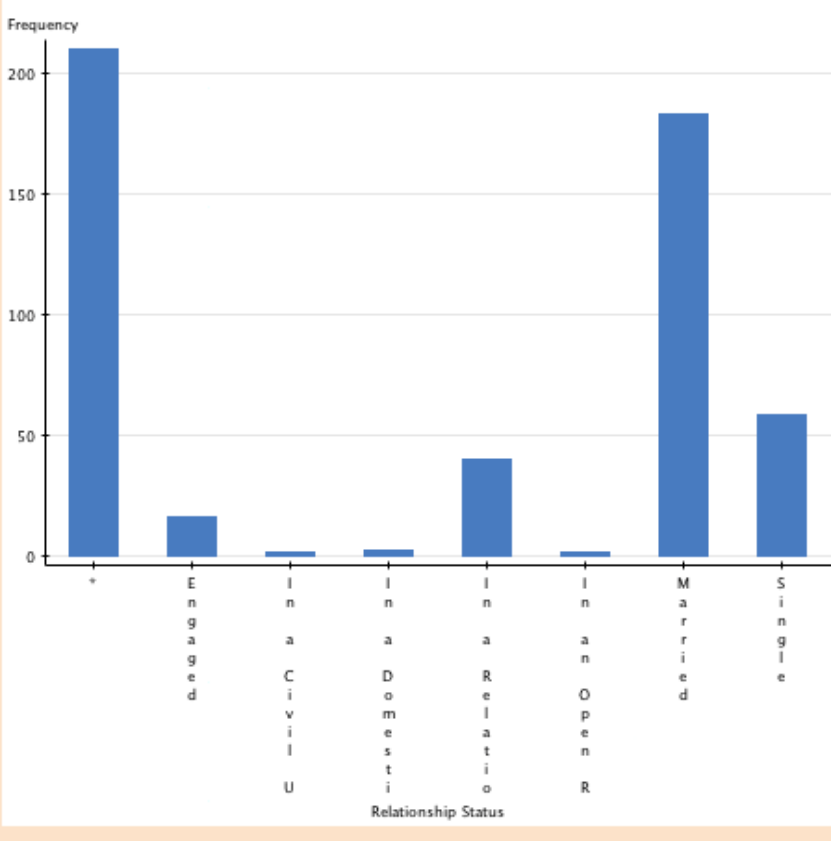


Figure 10. Bar chart of the relationship status of Jessica's *Facebook* friends

Another similar mishandling of the missing data was found in her project when Jessica conducted a hypothesis test based on her claim that more than half of her *Facebook* friends were married. To avoid non-

response bias, Jessica should have those who did not specify the relationship status on the *Facebook* accounts excluded from the population prior to the sample selection. Instead, using *StatCrunch*, Jessica selected a random sample of 100 *Facebook* friends. “Out of the 100 friends, only 54 chose to share their relationship status. The friends who did not share their relationship status were removed from the sample.”

For the interpretation of *y*-intercept of the regression model describing the relationship between her *Facebook* friend’s age and the number of wall posts on the page, she commented:

> *The y-intercept is the average value for y when x is zero. Since our scatterplot includes the values of zero for x (Age), we can find the y-intercept. Using the regression line, the value for wall posts (y) is 1243 for a person who is age 0. Now, age 0 has no real-world meaning, because a person of age 0 does not use Facebook. But since I did not exclude it from the scatterplot, it is meaningful to find it as the y-intercept as a way of understanding the average amount of wall posts.*

The inclusion of the age of zero does not justify that *y*-intercept is meaningful. Whether finding *y*-intercept is meaningful or not should be determined by its practical meaning. Furthermore, none of Jessica’s *Facebook* friends claimed an age of zero. Rather, Jessica mistakenly considered those friends who did not provide the age (missing data) was equivalent to having an age of zero.

As equally important as properly handling the missing data, one should have the consciousness of excluding the irrelevant data prior to data analysis. In response to the question posted in weekly discussions: For students who work, is there a linear relationship between the number of hours worked per week and the number of credit hours taken? Jessica failed to exclude those students who did not work.

b. Understanding statistical concepts and terminology

Terminology

The misusage of the statistical terms was found in several occasions of Jessica's postings. One type of the misusage of the terminology found in Jessica's postings was using the terms not defined in the course of statistics such as "sampling mean", "sampling distribution mean", and "mean proportion". The other type of the misusage resulted from the confusion between the terms. In making a comparison of the mean number of wall posts between male and female *Facebook* friends, gender and number of wall posts should be the explanatory variable and the response variable, respectively. However, Jessica erroneously stated, "using gender as the response variable and wall posts as the explanatory variable."

Jessica was confused with the statistical terms of count and proportion. In her project for inferring population proportions, Jessica defined the population parameter as "the appearance of the word 'Sarah' in the text" when it should be defined as the proportion of the word 'Sarah' appearing in the text. The confusion of statistical terms between

margin of error and standard error was also found in Jessica's posting: "The spread of the sampling distribution of the sample proportion is defined by the margin of error, or the standard error of the *p*-hat distribution."

Statistical Concepts

Jessica correctly used median and IQR to measure the center and variability, respectively, of a skewed distribution when learning Descriptive Statistics. However, IQR is a measurement describing the variation of, specifically, the middle 50% of the observations, not just any 50% of the observations as shown in the following posting: "The IQR is 318. So, 50% of the photos tagged to a *Facebook* page of a mosque that was surveyed in the US varied by as much as 318 photos." This same mistake was found again later in her project when Jessica described the variability of her *Facebook* friends' number of wall posts of their *Facebook* pages: "The IQR for the number of wall posts is 789. This tells us that the amount of wall posts each friend posted varies by as much as 789 posts." In the same project of analyzing her *Facebook* friends' number of wall posts on their *Facebook* pages, Jessica correctly used median as the center of wall posts. However, the median was incorrectly interpreted as a measurement of relative position:

> *For the quantitative variable 'Wall Posts', the exact middle value is 539 wall posts posted by Facebook friends. This means that 50% of*

friends posted to their wall fewer than 539 times and 50% of friends posted to their wall more than 539 times.

In Regression Analysis, Jessica understood correctly that the purpose of the coefficient of determination (r^2) was to evaluate the quality of the regression model: "We can use the model with a good degree of accuracy when predicting the amount of classes a student will take when given how many hours he or she will work." However, Jessica incorrectly explained the coefficient of determination of 72% as "the extent to which the *x* and *y* variables can be explained using the linear regression model."

Jessica understood the slope of the regression model and gave correct interpretation with appropriate context: "The slope of the regression line is -18.018574. This means that for every increase of one year of age we can see a decrease of about 18 wall posts." However, Jessica incorrectly related the slope to the correlation. Jessica commented on the slope of -18 as an indication of having "a weak linear regression." Although the sign of the slope agrees with the sign of the correlation coefficient, the magnitude of the slope does not provide the strength of the correlation.

A lack of solid understanding on the topic of sample mean distribution appeared in Jessica's posting. The mean of the sample mean distribution equals to the population mean. However, Jessica incorrectly stated that the mean of the sample equals to the population mean. "The

average lengths of the entire collection of lectures and the sample of 25 lectures have equal means of 86.79 minutes."

Jessica gave correct interpretation of the term standard deviation in learning Descriptive Statistics. She interpreted standard deviation of 29.44 minutes as, "Typically, the length of each lecture in the sample varies from the sample mean by about 29.44 minutes." Similarly, the standard error of the sample mean distribution should be interpreted as a typical distance from the mean of all the sample means. However, Jessica inaccurately interpreted it as the variation among the sample means: "The standard error is 5.154 minutes. This means that, if all the samples of size 25 were taken from the entire *iTunes* lecture collection, the mean values of all the samples would vary by about 5 minutes in length." However, the mistake was corrected later in the project. Jessica accurately interpreted the standard error of the sample mean distribution: "In context, this means that, if a sufficient amount of samples of size 30 are taken from the population and the mean is found for each sample, on average, the means of the various samples will vary from the population mean by about 152 wall posts."

Jessica mistakenly described the *p*-value as a regular probability when *p*-value should be a conditional probability. "The *p*-value is a probability of stating that more than 50% of Muslims from the 27 countries believe the story of Osama bin Laden's death to be untrue." Even though Jessica did not describe the *p*-value correctly, she understood

clearly the difference between the significance level and the *p*-value: “The *p*-value represents the probability of making a Type I error and is computed from the sample results as opposed to the prescribed probability of the significance level chosen in the beginning [of the test].”

Jessica’s understanding of the confidence level was vague. This vague understanding was found when Jessica constructed confidence intervals using two different confidence levels, 95% and 99%. Jessica made the following comment regarding the two different confidence levels: “The confidence interval at 99% is going to be much more accurate but a little less precise than the confidence interval at 95%.” A higher confidence level does not lead to a higher level of accuracy, rather, a higher level of reliability. The confidence interval constructed with a confidence level of 99% is one of the many possible intervals one could get. As explained later by Jessica, “There is no way for me to know for sure if the [confidence interval constructed from the] sample chosen was [the one] that captures the true population proportion.” Therefore, a higher confidence level does not determine a higher level of accuracy. However, a higher confidence level does lead to less precision due to a wider interval vs. a narrower interval produced from a lower confidence level, hence, higher precision from a lower confidence level.

Finally, the misconception of ‘proving’ the null hypothesis to be true or untrue as a result of hypothesis testing on a parameter appeared repeatedly in Jessica’s projects. Testing or estimating for the purpose of

inferring a population parameter cannot and should not be used to ‘prove’ the truth-value of the parameter. In testing the population mean, Jessica stated, “I wish to claim that the average age of all of my *Facebook* friends is younger than 35 years old. Thus, the presumption is that the average age is 35 years old, which defines the null hypothesis. Since I wish to prove otherwise, the alternative hypothesis is the case where the average age, or mean age, is less than 35 years old.” When comparing the difference between two population means through a hypothesis test, Jessica explained, “For testing purposes, I wish to prove that there is a difference between the amount of posts posted by males and the amount posted by females.” The misconception of being able to ‘prove’ through a hypothesis test appeared again when she explained her reason of conducting a hypothesis test over constructing a confidence interval, “because I was more interested at first to see if there was a statistically significant result to prove the null hypothesis that there is no difference between married female and male *Facebook* friends.”

c. Interpreting statistical results using non-technical and layman’s terms with context

Context

In the beginning of the course, Jessica had difficulty including the context when interpreting the statistical results. For example, in describing the center of the data when analyzing the bar chart of a qualitative variable Popular Week (Figure 2), she failed to include the context of the variable

Popular Week. “Looking at the bar chart for Popular Week, one can see the center of the data, as defined at the category that occurs the most, is at 07/15/12. The other week with a high frequency is 12/16/12.” This issue of lacking the context continued in the following week when describing the frequency of “60 times” from analyzing the histogram of a quantitative variable (Figure 3). “This indicates that most of the values for the amount of photos tagged to a certain mosque on *Facebook* were between 0 and 500 and occurred 60 times.” Later, in reviewing the sample distribution, Jessica explained why the mean was used to describe the center; however, no context of the mean was included: “Since the shape is symmetric, the mean is used to describe the center and that value is 90.04 minutes.”

Correct interpretation with the inclusion of context was found toward the end of the study period when testing the mean lecture length of the lectures collected in *iTunes* library, the null hypothesis is that the mean lecture length is 80 minutes while the alternative hypothesis is that the mean lecture length is longer than 80 minutes long. Using context, Jessica gave correct interpretation of Type I error and Type II error: “a Type I error would occur if a conclusion was made stating that the mean lecture length of the entire *iTunes* library collection was not 80 minutes long when in fact it was 80 minutes long. A Type II error would occur if a statement was made concluding the mean lecture length of the entire *iTunes* collection was 80 minutes in length when in reality the mean was greater than 80 minutes in length.”

2. Findings associated with statistical reasoning

    a. Understanding statistical processes

Randomization and Normality Assumptions

Randomization and normality assumptions are required for making inferences on population means or population proportions through either constructing confidence intervals or conducting hypothesis tests. A clear understanding of the requirements can be seen in her project posting. Jessica explained the satisfaction of the randomization requirement: "Since the *StatCrunch* was used to produce random numbers, the sample being used is random." She continued to describe the satisfaction of the normality requirement.

> *The normality assumption is a requirement that the sample mean distribution follows a normal distribution. The population distribution being used is not a normal distribution, so the sample size must be at least 25. The sample size being used is 30, so the sample mean distribution will indeed follow a normal distribution.*

However, before the project submission on the same topics, Jessica struggled with the normality assumption requirement in her weekly discussions. The requirement of the normality assumption when making inferences on a population mean refers to the requirement of a bell-shaped symmetric sample mean distribution. Jessica erroneously referred the requirement of a bell-shaped symmetric distribution to a sample distribution. In addition, the large sample size requirement (with the

sample size being at least 25) is needed only if the distribution of the population does not follow a normal distribution. Jessica posted the weekly discussion on the requirement of normality assumption when inferring population mean through constructing a confidence interval:

> *The first requirement is normality assumption. As seen by the histogram, the sample follows a somewhat normal distribution. The second requirement is the size of the sample given the distribution is not normal. The sample size in this case is 25, the minimum requirement. So, if the sample distribution had not been normal, or if it is not perfectly normal, the sample still meets the requirements for producing a 95% confidence interval*.

In the following week on conducting a hypothesis test on a population mean, the same incorrect understanding about the normality requirement was found in Jessica's weekly discussion: "Normality assumption states that the population distribution must be symmetric in order for the sample distribution to be symmetric."

Even though the concept of normality assumption requirement for making inferences on population means was corrected in her project submission as shown earlier, it appeared incorrectly stated with similar mistakes when Jessica discussed the normality assumption requirement for making inferences on population proportions. Similar to the normality assumption for making inferences on population means ensures the sample mean distribution following a normal distribution, the normality

assumption requirement for making inferences on population proportions ensures the sample proportion distribution following a normal distribution. However, Jessica incorrectly explained that the normality assumption requirement was “for the sample to follow a normal distribution”.

b. Being able to interpret statistical results

Descriptive Statistics

The analysis of a variable in a data set begins with the recognition of the data type of the variable. Since qualitative data have no numerical values, it was incorrect to describe the shape of the distribution from a bar chart (Figure 2) as depicted in her posting. “The distribution of the data occurs evenly throughout the graph and does no fall heavily to one side or the other.” In the following week when analyzing the histogram of a quantitative variable, Jessica did not know what to look for from the graph and was uncertain how to approach the discussion of extreme values.

Regression Analysis

Jessica had difficulties analyzing regression outliers and clusters from a scatterplot due to her not having a thorough understanding of the terms. Mistreated the observations as one-variable data set, Jessica incorrectly described the observation “over 40 hours of work with under 5 hours of classes taken” found on the scatterplot (Figure 6) as “a potential outlier” because “compared with the rest of the data, we can see this value is unusual”. Jessica went on to conclude that “there are a few clusters on

the scatterplot but nothing very dense" even though there were no clusters shown on the scatterplot.

As in the weekly discussions described above, Jessica showed the same difficulties in recognizing regression outliers and clusters from a scatterplot in the project discussions due to her lack of full understanding of the statistical terms. In the project, Jessica was interested in knowing if the age and the amount of wall posts of her *Facebook* friends were associated. From the scatterplot (Figure 11), Jessica showed her understanding of the regression outliers being the observations away from the trend. However, she failed to recognize from the scatterplot that the outliers were the individuals with ages between 20 and 30 and having more than 3000 wall posts. Rather, she concluded, "It does not appear as though the scatterplot contains any regression outliers, because no value is away from the general trend."

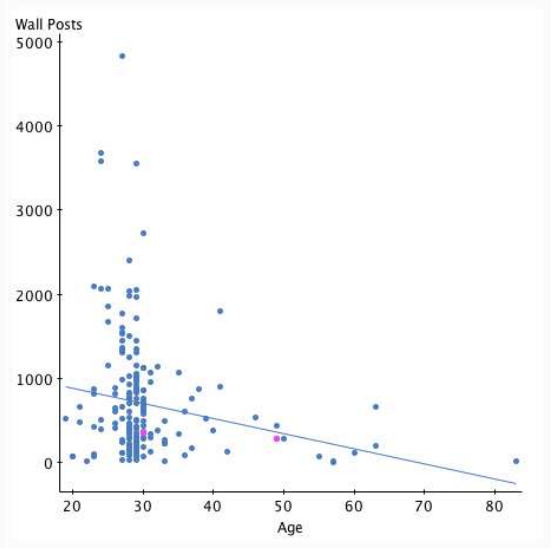


Figure 11. Scatterplot of age and wall posts of Jessica's *Facebook* friends

Next, Jessica described the clusters appeared in the scatterplot as follows: “The scatterplot does show several clusters. Many values appear at age 30 and with wall posts numbering less than 500. Also, strong clusters occur at age 30 with wall posts around 1,000 and also 2,000.” There were two clusters found in the scatterplot produced from Jessica’s *Facebook* friends. But unlike what Jessica described, one cluster contained the majority of the observations that were following the negative trend indicating that the older the individual was, the fewer number of wall posts on his/her *Facebook* page. The other cluster appeared on the scatterplot was the group of those regression outliers. Those regression outliers were the individuals who were between the age of 20 and 30 but with much more number of wall posts (more than 3000) on their *Facebook* pages than the other *Facebook* friends who were between the age of 20 and 30 with fewer than 3000 wall posts on their *Facebook* pages. In addition to the incorrect description of the clusters, it seemed that Jessica used the term ‘strong clusters’ to describe the clusters as containing many observations. There is no classification of a cluster in terms of its strength. A cluster containing many observations does not make it a strong one. Likewise, a cluster containing fewer observations does not make the cluster a weak one.

Jessica showed correct understanding of the statistical results and correct interpretation of the negative trend displayed on the scatterplot. In regard to the negative trend, Jessica stated, “This indicates that when

students worked less, they enrolled in more classes and when students worked more, they enrolled in fewer classes." The slope of the regression model was also correctly interpreted. The following posting was found in the weekly discussions where Jessica stated,

> *The slope of the regression line between amount of work hours and the amount of class hours is -.445632. Since the scatterplot displays a negative correlation between the two variables, it makes sense that the slope is negative. This means that for each increase of one hour of work, there will be a .445632 hours decrease in the amount of class hours.*

Inferential Statistics

Jessica correctly interpreted the statistical results of confidence intervals for estimating population means in her weekly discussions: "With 95% confidence, I can conclude that the mean of all the lectures in Ms. Miao's iTunes library, given by Shaykh Riyadh, are between 77.89 minutes and 102.20 minutes in length." The correct interpretation of confidence interval results for estimating population means was also found in her project posting, "With 95% confidence, I can conclude that the mean amount of wall posts posted by my *Facebook* friends is between 413 wall posts and 743 wall posts." However, Jessica showed difficulties in interpreting the confidence interval results when comparing the difference between two population means. With an interval of (-6830, 40961), one should conclude with an insignificant difference of the mean number of

views between SmartGirl's and Mufti Menk's *YouTube* channels. Specifically, the difference of mean number of views between the two channels could be somewhere between 6830 fewer and 40961 more views on SmartGirl's *YouTube* channel than on Mufti Menk's *YouTube* channel. Rather, Jessica concluded, "there is a significant statistical result indicating that the mean number of views of the SmartGirls channel is -6830 to 40961 views more than Mufti Menk's channel."

When making the decision of rejecting or not rejecting the null hypothesis from hypothesis testing results, one compares the *p*-value with the prescribed level of significance. The level of significance is served as a threshold to maintain the quality of the test in terms of the probability of making a Type I error. When one wishes the probability of making a Type I error to be no more than 5%, the level of significance will be set up at 5%. Therefore, if the probability of a Type I error computed through the sample evidence (*p*-value) is higher than 5%, one should not reject the null hypothesis to avoid making a Type I error. Jessica demonstrated her clear understanding of making decision when the *p*-value is much higher than the level of significance. She posted the following in her weekly discussion when testing the population mean:

> *The p-value is much greater than the significance level chosen at the beginning of the hypothesis testing procedure. The risk of making a Type I error is much too high. Thus, the mean of the 30 lecture lengths taken from Ms. Miao's iTunes collection, 82.53 minutes long,*

is insignificant to conclude that the population mean length of the iTunes collection is longer than 80 minutes long.

However, Jessica would violate the rejection rule when *p*-value was close to the level of significance even though *p*-value was larger than the prescribed level of significance. As discussed in her project when testing the population mean age of her *Facebook* friends, Jessica stated: "The *p*-value given through calculation is 0.0591, which is pretty much the same as alpha at 5%. Thus, the mean of the sample of 30 of my Facebook friends is statistically significant to conclude that the population mean of all of my *Facebook* friends is younger than 35 years old." The same mistake was repeated when Jessica compared the proportions of her married female *Facebook* friends and married male *Facebook* friends in her project where the *p*-value was found to be 0.0546. Due to its value larger than the prescribed level of significance at 5%, one should not reject the null hypothesis. However, Jessica claimed, "the *p*-value is low" and made an incorrect conclusion by rejecting the null hypothesis.

3. Findings associated with open-ended interview and summary

The open-ended interview question assigned to Jessica was related to Regression Analysis (Appendix M). Jessica's reply to the first part of the interview reflected her capability of thinking statistically. In particular, Jessica was able to view the entire statistical process as a whole and knew how and what to investigate through the context.

The appropriate statistical analysis procedure is regression analysis. Since the health expert wishes to find a link between fiber content in breakfast cereals per gram and the amount the cereals costs per cup, the best procedure is to construct a regression model. The two variables in question are both quantitative variables, thus further proving the eligibility for a regression model. The health expert can then make predictions about fiber content and expected cost to the consumer, if the two variables are linearly correlated.

Two questions were posted in the second part of the interview to examine Jessica's statistical reasoning capability. In responding to the strength of the correlation between the two variables posted in the first question, Jessica analyzed the correlation correctly from the perspective of a scatterplot followed by a quantified correlation coefficient (*r*).

Looking at the scatterplot alone offers little confidence that the fiber content of the 18 cereals and their costs are correlated. However, looking closely, it is clear that as cost goes up on the x-axis, fiber content also increases on the y-axis. It is because of this relationship that I believe that the two variables share a positive linear correlation. Now looking at the simple linear regression results, one can be certain that the two variables share a weak positive linear correlation. I know this is true because the R value (correlation coefficient) is .2415. The value of R is low and positive, thus confirming the weak positive linear correlation between the fiber content in grams per cup and the cost in cents per cup of the cereals.

Jessica continued to comment on the advice that a health expert could provide to her client using the regression model produced. In replying to the second question, Jessica wrote:

> *I would tell the health expert that the regression model is moderately good at predicting the amount of variation of the fiber content in the cereals based on the cost of the cereals. The R-squared value is .5831869, or 58%. This indicates that only 58% of the variation of the two variables can be explained by this particular regression model. 42% of the variation cannot be accounted for through this regression model. This means that predicting the amount of fiber content in the cereal based how much the cereal costs will not result in a highly accurate result. The negative results of trusting a regression model with a moderate or low coefficient of determination (R-squared) is, in this case, an overestimation or underestimation of fiber content per cost.*

After prompting for more clarification of "The negative results of trusting a regression model with a moderate or low coefficient of determination (R) is, in this case, an overestimation or underestimation of fiber content per cost", Jessica replied,

> *I mean that if the regression model is not that accurate, it would be difficult to tell a consumer willing to pay 60 cents per cup of cereal that she will get so many grams of fiber in her box of cereal. She could be getting way less or way more. An underestimation seems like the outcome the health expert would want to avoid. An underestimation means that she*

would be paying 60 cents per cup and getting less fiber than what the regression model predicted.

Jessica's replies to both questions posted in the second part of the interview demonstrated her competence of reasoning statistically. Her replies reflected the clear understanding of the process as well as her capability of interpreting the statistical results. However, Jessica misread the value of r^2 of 0.058 (5.8%) as 0.58 (58%). Due to the mistake, Jessica commented the regression model as "moderately good" when in reality, using the regression model for estimation should be considered as having a poor quality.

In summary, Jessica's overall interview results revealed her competence in her conceptual understanding in terms of statistical literacy, reasoning and thinking. Specifically from the interview results, it was noticeable that Jessica established her data consciousness of recognizing the data type prior to the data analysis. Perhaps, the biggest achievement for Jessica throughout the study period was being able to communicate the statistical results using context in non-technical terms.

Summary

Chapter four presented the data analysis results of participants' conceptual understanding via the data collected from TALQ survey, CAOS assessment, postings from online weekly discussions and topical projects, and open-ended interviews conducted at the semester end. The quantitative data analyses including summary statistics of the TALQ survey and CAOS assessment, and regression analyses between TALQ scales and CAOS score were performed and analyzed. The possible indications of

the findings were discussed. Content analysis was conducted in analyzing postings from online weekly discussions, topical projects, and interviews. Quantitative descriptions of intra-coding and inter-coding agreement rates were computed and displayed. The overall effectiveness of implementing Merrill's First Principles of Instruction was analyzed through statistical tests results performed on the coding results between the weekly discussions and the topical project submission. Percentages of "clear understanding" coding from interviews were also calculated and analyzed. Finally, a detailed qualitative description of cognitive development toward conceptual understanding in terms of statistical literacy, reasoning, and thinking was presented through a selected purposeful sample of participants.

Chapter 5

Conclusions, Implications, Recommendations, and Summary

Conclusions

For the purpose of understanding how the course design based on First Principles of Instruction can facilitate tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment, a case study was conducted in a blended introductory statistics course at a two-year college in Greater Los Angeles area in Spring 2013. Three research questions guided the study:

1. How do Merrill's First Principles of Instruction guide the development of an introductory, technology-enhanced, statistics course?
2. How can *StatCrunch*, a web-based social data analysis site, be used to support meaningful learning?
3. How does statistics instruction designed according to Merrill's First Principles improve teaching and learning quality (TALQ) and develop statistical conceptual understanding?

This section will answer the three research questions based on the observations, the statistical results, and the content analysis results collected and analyzed from the case study.

Research Question 1: How do Merrill's First Principles of Instruction guide the Development of an Introductory, Technology-Enhanced, Statistics Course?

Using Merrill's Pebble-in-the-Pond instructional design approach, instructional instances on the topics of Descriptive Statistics (including Regression Analysis), Sampling & Inferences on Population Means, and Sampling & Inferences on Population Proportions were designed with an emphasis placed on real-world whole tasks and the development of the four phases of learning: Activation, demonstration, application, and integration. Real-world whole tasks were designed mainly utilizing data gathered from social networking sites (e.g. *Facebook*, *iTunes*, and *YouTube*). Prior to the discussion of each topic, readings on related topics were assigned to the students. For the activation phase of learning, the assigned readings for the current topic along with the content learned from the previous lessons enabled students to activate relevant previous experience when learning through the modules. For the demonstration and application phases of learning, real-world examples were demonstrated in the weekly modules for the materials covered followed by weekly forum discussions. Weekly forum discussions were designed to provide students opportunities to apply their new knowledge and skills to solve problems similar to the examples demonstrated in the modules. Finally, a topical project after each course topic delivered was designed to allow students to integrate their statistical skills to statistically analyze the profiles of their *Facebook* friends.

The course topic of Sampling & Inferences on Population Means was divided into three parts: Part I – Sample Mean Distribution & Confidence Interval for the Population Mean, Part II – Significance Test for the Population Mean, and Part III – Comparing Two Population Means. These three parts of the topic were delivered in three weeks, namely, the ninth, the tenth, and the eleventh week of the semester. As an example to illustrate how Merrill's First Principles of Instruction were implemented in developing the

instructional instances, the course design of the weekly module of Part II – Significance Test of the Population Mean, delivered in the tenth week is described in greater depth as follows.

The tenth weekly module covered the topic of hypothesis testing for population means. Figure 12 shows a screenshot of the Table of Contents of the tenth weekly module. Specifically, the tenth weekly module discussed the imbedded presumption in conducting a hypothesis test (Appendix N), followed by a description of a four-step process with a complete guided real-world example (Appendix O).

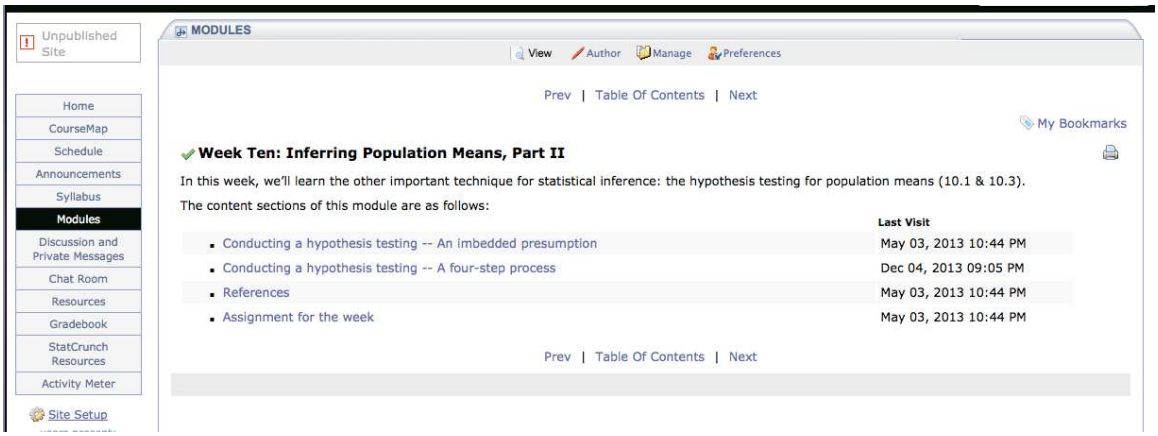


Figure 12. Screenshot of week ten module: inferring population means, part II – Table of Contents.

Real-world tasks.

As suggested in the Pebble-in-the-Pond approach, the first step in the course design is to clearly specify the complete task needs to be solved (Merrill, 2002). As shown in Appendix O, the complete problem was identified and clearly stated in the guided example before showing the steps required for solving the problem. The data used in the guided example were obtained from the researcher's *iTunes* library where 59 lectures

were collected with various lengths ranging from 17.73 minutes to 167.88 minutes. Rather than using fabricated data, the real-world data set of 59 lecture lengths was used as the base of the extended population in the guided example. Through complex and ill-structured problems, students gain the experience of handling the messy nature of the real-life data (Merrill & Gilbert, 2008). Although there were no missing data involved in the data set, some lectures were split into more than one audio file due to the capacity limitations of the technology. Since the task was testing the mean length of the lectures, students were aware that the different parts of the same lecture should be combined prior to the data analysis. In order for *StatCrunch* to perform analysis, students were alerted that the recording time should be converted from hour-minute-second format (e.g. 1:22:52) used in *iTunes* into minutes. Issues related to handling real-world tasks continued in the topical project when students analyzed the variables of their choice of their *Facebook* friends. Prior to sample selection, the missing values should be excluded to avoid sampling bias. It was through constant exposure to the "unclean" real-life data that students developed data consciousness, an important aspect of statistical literacy.

Activation phase.

Students were instructed always to read the related chapter and sections covered in the textbook prescribed prior to the studying of the weekly modules. For the topic of Significance Test for the Population Mean, students were instructed to read 10.1 and 10.3 of the assigned Sullivan (2010) textbook. Furthermore, the course material of significance tests was relevant to confidence intervals delivered in the previous week in that both methods were used in making inferences of the population parameters. Students were reminded that both methods require the sample mean obtained from the sample

selected randomly from the population to make an informed decision about the unknown population mean. Specifically, a confidence interval estimates the population mean while a significance test is used to support or not to support a claim made with respect to the population mean (Appendix N). Specifically, the random sample of 25 lecture lengths used for conducting the hypothesis test in the guided example was the same as the sample used in the previous weekly module for constructing the confidence intervals. With the same interpretation of the statistical results obtained through constructing a confidence interval (as learned in Part I) and conducting a hypothesis testing (as learned in Part II), the relevant previous experience students gained from constructing a confidence interval could be activated when learning the topic of hypothesis testing. With a *p*-value of less than 0.0001 obtained through the hypothesis test, one could conclude that the sample evidence was significant to support the claim that the mean lecture length in the researcher's *iTunes* collection was longer than 60 minutes (Appendix O). This result agreed with a 95% confidence interval of (76.5, 98.4) constructed in the previous week where the interval was interpreted as, "With 95% confidence, the mean lecture length in the researcher's iTunes collection was between 76.5 minutes and 98.4 minutes." Since the interval covers the length greater than 60 minutes, it coincides the significant result obtained through the hypothesis test.

Demonstration phase.

The guided example given in the module used the data set of 59 lecture lengths collected from researcher's *iTunes* library. Using the same random sample of 25 lecture lengths selected for constructing a confidence interval, a hypothesis test was conducted to test the claim that the mean lecture length of the *iTunes* collection was greater than 60

minutes. The example demonstrated how to conduct a hypothesis test following the four-step process adopted from Gould and Ryan (2013). The four steps of the hypothesis test were to hypothesize, prepare and get ready to test, compute to compare, and make decision and interpret. A detailed explanation of each step of the hypothesis test was discussed for the purpose of developing students' conceptual understanding. Rather than merely showing how to "do" the problem, the interpretation with the context using non-technical terms was emphasized in the demonstration. After setting up the two hypotheses and going through the lengthy preparation step, the computation was performed through the usage of *StatCrunch*. Finally, the decision of the test was made and the interpretation of the statistical results obtained from hypothesis test in layman's terms was addressed (Appendix O).

Application phase.

Using the same collection of lectures collected in researcher's *iTunes* library as shown in the guided example in the weekly module, students were asked to apply the statistical analysis skills learned in the module to conduct a hypothesis test that the population mean lecture length of the collection was greater than 80 minutes through their own random sample selections. Appendix P shows the instructions of conducting a hypothesis test given for the online weekly discussion. The screenshot of the weekly discussion forums for the topic of Inferring Population Means is displayed in Figure 13. Students posted and shared their results of hypothesis testing in the weekly discussion forum. Learning is promoted when learners are engaged in sharing experiences (Merrill & Gilbert, 2008). Through different sample results due to distinctive samples, students experienced various *p*-values ranging from as low as 0.01 to as high as 0.22. This hands-

on experience allowed students to practice the skills learned from the module. Students learned that statistical analysis was a scientific method used to make decisions about the unknown population parameter. In addition, through the sharing of their postings and discussions, students experienced the differences of the results due to the uncertainty of the unknown characteristics of the population parameter.

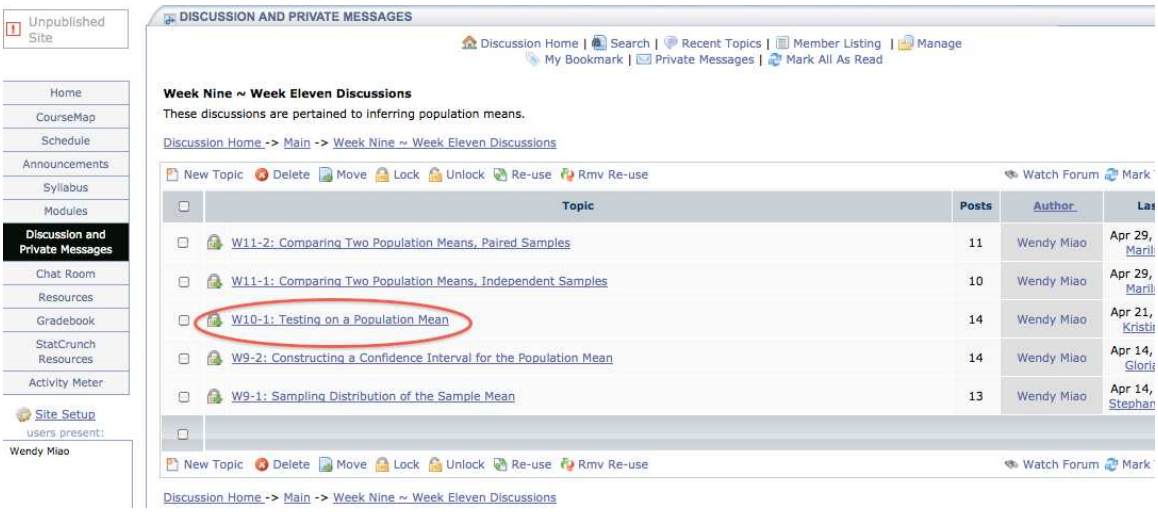


Figure 13. Screenshot of weekly discussion forums

Integration phase.

Finally, the integration phase of learning was promoted through a comprehensive topical project that required students to apply the materials learned in all three parts, Part I – Sample Mean Distribution & Confidence Interval for the Population Mean, Part II – Significance Test for the Population Mean, and Part III – Comparing Two Population Means, of the topic of Inferring Population Means to perform the necessary statistical analyses on the variables of their choice of their *Facebook* friends' profiles. Appendix Q shows the three parts of the project assigned to students after the completion of the topic of Sampling & Inferences on Population Means. Similar to weekly discussions, a Project

for Inferring Population Means forum was set up and allowed students to share, post, critique, and defend with one another to promote learning (Figure 14).

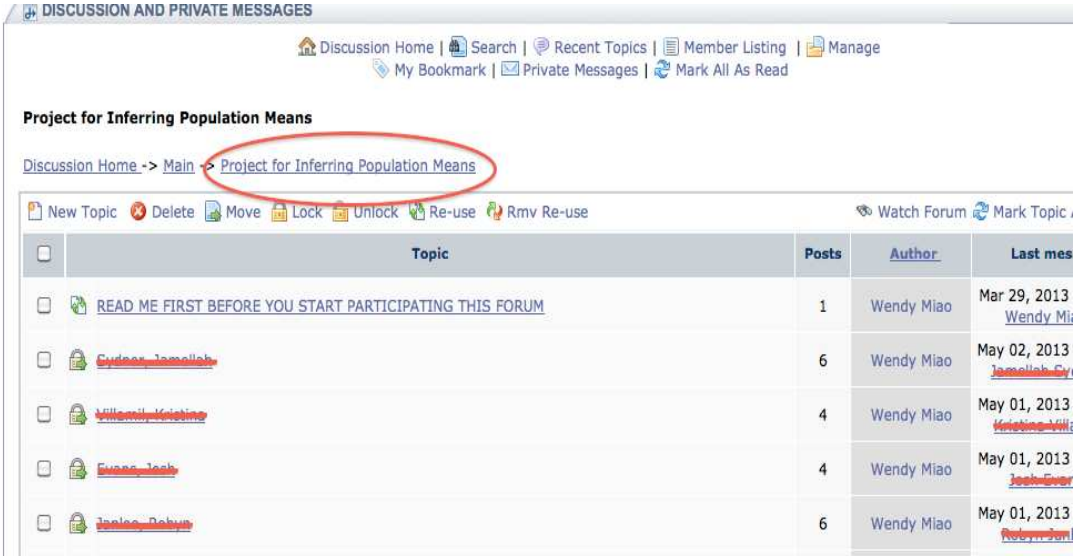


Figure 14. Screenshot of project for inferring population means discussion forum

Research Question 2: How can StatCrunch, a Web-Based Social Data Analysis Site, be Used to Support Meaningful Learning?

The concept of technology being part of the statistics curriculum was reinforced when Moore (1997) recommended the reform of statistics education in terms of content, pedagogy, and technology. Being proficient in using technology has now become a required skill when learning statistics. The concern was which statistical package to choose. One of the reasons that *StatCrunch* was selected to facilitate the instruction in the present case study was its capability of setting up user groups that allowed the sharing with one another within the groups (West, 2009). Prior to the start of the semester, a class group was set up where common data files used in the modules and discussion forums were shared among the group members. Students were required to join the class group and learn how to navigate the site for future sharing of their own data and charts. The

StatCrunch training included in the first week module demonstrated how to join the class group, leave comments for the group, and uploading and saving a data file. The link to the resources for using *StatCrunch*, in particular, *StatCrunch* YouTube channel where many videos showing the usage of almost all the features available on *StatCrunch* was also provided in the training. The easy-to-use interface of this web-based software package allowed students to navigate the site without much difficulty after the training. Figure 15 displays the screenshot of the class group where data sets, results, and comments were shared among the group members.

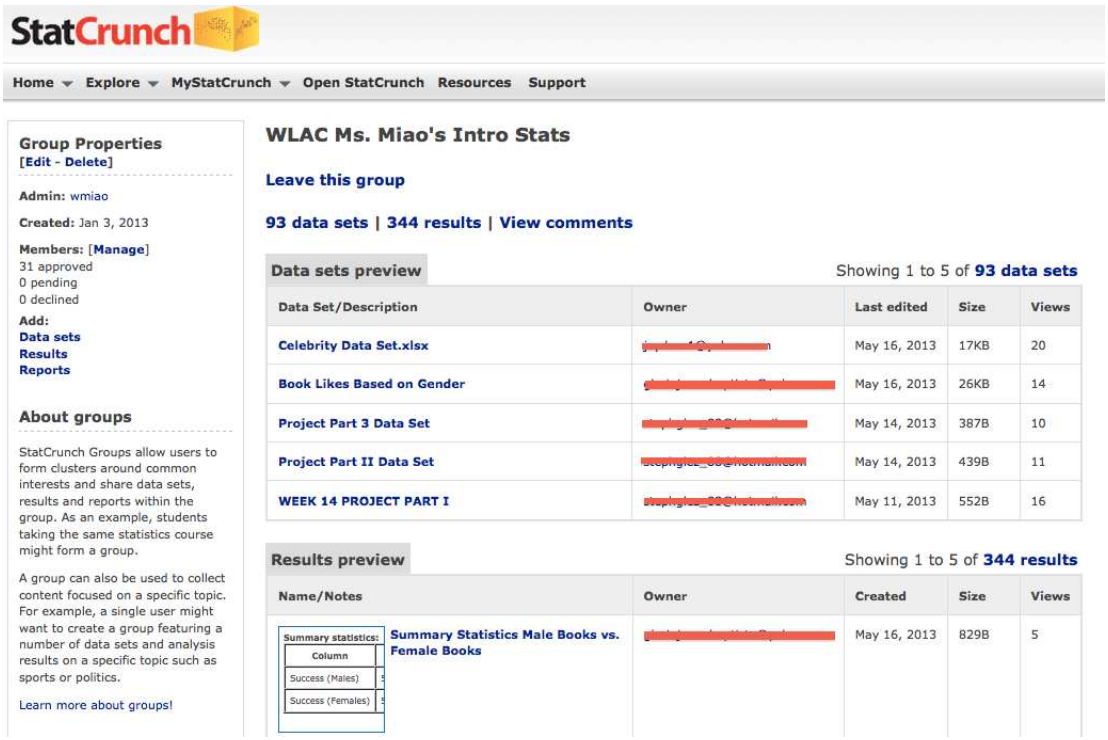


Figure 15. Screenshot of class group on *StatCrunch*

Choosing technology to use in statistics education serves the purpose of *doing* statistics and/or *understanding* statistics (Baglin, 2013). According to Baglin, *doing* statistics refers solely to drawing statistical graphs and finding numerical results through

computation. Although *doing* statistics contributes to the understanding of statistics, the term *understanding* statistics used by Baglin confines to understanding statistical concepts without *doing* statistics through computation, such as the use of Applets. *StatCrunch* enables the students to both *do* and *understand* statistics. How the usage of *StatCrunch* supported meaningful learning in the present case study in regard to *doing* statistics and *understanding* statistics is described below.

Strengthening statistical concepts through doing statistics.

a. With the ease of using technology to produce graphs and numerical statistical results, students learned to contemplate the context of the data for drawing meaningful and relevant contextual conclusions: Having data awareness is one of the components necessary for developing statistical literacy. When exposing oneself to the real-life data, the messy nature of the data forces the individual to reexamine the data and thus, establish data consciousness. The ease of technology expedites the process of data consciousness establishment. When learning the course topic of Regression Analysis, a data set of 100 students with their work hours and credit units taken for the semester was presented. Participants were asked to analyze the correlation between the work hours and the semester units taken for *those students who work.* After identifying the explanatory variable (work hours) and the response variable (semester units), students produced scatterplots using *StatCrunch* and posted on the class group to share their results. The researcher also posted a scatterplot with sample correlation coefficient results on the discussion forum (Figure 16). One participant first noticed that the sample correlation coefficient (-0.57) obtained from the other participants as well as hers

was different from the researcher's result (-0.85). This prompted an investigation among the participants to explore the reasons for the difference. During the investigation, another participant noticed that their scatterplot results (Figure 17) were not the same as posted by the researcher. A new round of discussions arose. Soon afterwards, participants reached to a consensus that the data to be analyzed should be confined to only *those students who work*. With a few clicks on the *StatCrunch*, students easily and quickly reproduced correct scatterplots. The ease of the technology reduced the possible frustration experienced by the learners during the process of learning and trying. The positive and quick feedback through the use of *StatCrunch* assisted the learners to focus on the development of data consciousness in terms of the awareness of cleaning up the messy nature of the real-life data prior to data analysis. The development of data consciousness was observed as the semester progressed. In particular, in analyzing their *Facebook* friends' profile for the topical projects, participants consciously excluded those friends who did not specify the information from the analysis.

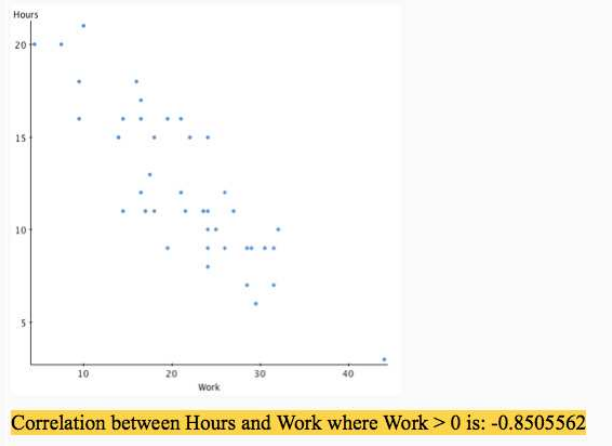


Figure 16. Scatterplot produced by the researcher

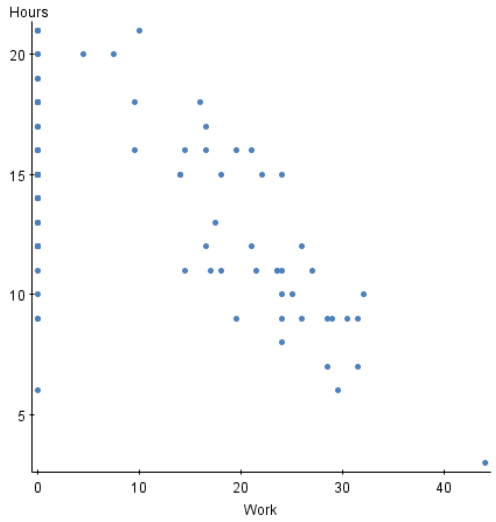


Figure 17. Scatterplot produced by the students

b. With the ease of using technology to compute summary statistics, statistical terms can be understood through the use of the formulas and verified using technology: Relying on *StatCrunch* for doing statistics does not mean abandoning the teaching of the formulas. Formulas are served as the means of understanding statistical terms. Statistical concepts are established upon a sound understanding of the statistical terminology. However, clear understanding of statistical terms has always been a great challenge to the students learning Introductory Statistics. To combat this challenge, formulas were used to explain the concept while technology was used as verification of the concept due to its rapidness of obtaining the numerical results. On the topic of inferring population parameters through estimation, the concept of reliability and precision of a confidence interval was illustrated using both formulas and *StatCrunch*. In addressing why, in general, the precision of a confidence interval of a population mean could be

reduced with high level of reliability, the formula of the margin of error ($m = t_{\alpha} \frac{s}{\sqrt{n}}$) was used to justify the reason. This theory was then verified by comparing three confidence intervals each constructed at a different confidence level of 90%, 95%, and 99%, respectively. With a few clicks, the three confidence intervals were constructed using *StatCrunch* to visualize how the precision was reduced as the confidence level was increased (Figure 18).

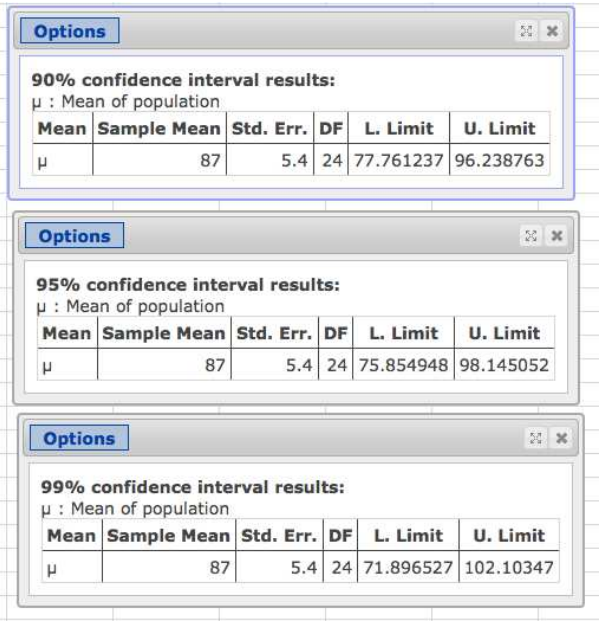


Figure 18. Confidence intervals produced by *StatCrunch* at various confidence levels

c. With the ease of using technology, focus can be placed on pondering questions to improve statistical reasoning rather than busying oneself with doing computation manually: The course of introductory statistics involves computing statistics through long formulas. Without using the technology such as *StatCrunch*, students could spend much time to focus exclusively on getting a correct answer without spending time contemplating the entire statistical process and the

interpretation of the statistical results. Using *StatCrunch*, students obtained the statistical results through few clicks and busied themselves with the reasoning and the interpretation of the statistical results. The use of technology enhances students' development of statistical reasoning (Biehler, Ben-Zvi, Bakker, & Makar, 2013). Through the usage of *StatCrunch*, students' cognitive load was released from computation and graph drawing for strengthening their statistical concepts through pondering questions such as:

- Explain why we cannot describe the distribution of a qualitative data set in terms of its shape, number of mounds, and unusual values.
- What is the probability that a 95% confidence interval captures the sample mean lecture length calculated from the sample?

d. With the ease of using technology to draw random samples, challenging statistical concepts on the topic of sampling distribution in terms of $\mu_{\bar{x}} = \mu$ and $\sigma_{\bar{x}} = \frac{\sigma}{\sqrt{n}}$ can be overcome using the technology: In the study, the concept of sample mean distribution was demonstrated through both *doing* statistics and *understanding* statistics. The aspect of *understanding* statistics was using the applet to deliver the concept while the aspect of *doing* statistics was through computation, specifically, computing sample means of the samples collected randomly from the population. The applet used in delivering the concept of sample mean distribution will be detailed in the next section. This section presents how students learned sample mean distribution through *doing* statistics.

Sampling distribution, involving repeated sampling from the population, is a challenging yet vital concept in learning inferential statistics. Utilizing the Sample function built in *StatCrunch* for random sample selection eases the learning of sampling distribution (Figure 19). Selecting random samples is tedious without technology. Depending on the sophistication of the technology, drawing random samples may require manually inputting the data, which could be a time-consuming process. Using *StatCrunch*, random samples of specified sizes could be drawn in few clicks.

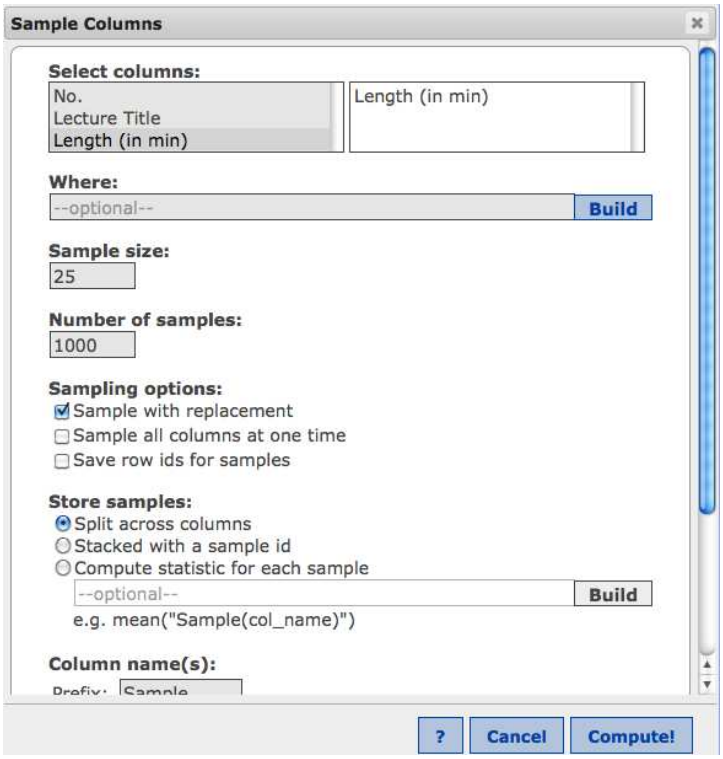


Figure 19. Sample built-in function on *StatCrunch* for selecting random samples

When learning sample mean distribution, students learned that, according to the Central Limit Theorem, the mean of the sample means computed from all the samples with the same specified sample size selected from the population should

be the same as the population mean while the standard deviation of the sample means computed from all the samples with the same specified sample size selected from the population should be $\sigma/\sqrt{n}$ where σ is the population standard deviation. To illustrate the concept, one thousand random samples of a sample size of 25 each were drawn from the population of lectures collected in the researcher's *iTunes* library. Using the built-in Summary Stats on *StatCrunch*, 1000 sample means from the 1000 samples drawn were computed and displayed in a list (Figure 20). The sample mean lecture lengths computed from 1000 samples varied from 72.96 minutes to a maximum of 107.23 minutes. Students were asked to apply Central Limit Theorem to estimate the possible numerical values of the mean and the standard deviation of the 1000 sample means given that the population mean lecture length was 86.79 minutes with a population standard deviation of lecture length of 25.77 minutes. Figure 21 displays that the mean of the sample mean lecture lengths was 87.12 minutes with a standard deviation of the sample mean lecture lengths of 5.12 minutes which verified Central Limit Theorem that the mean of the sample means should be the same as the population mean (approximately 87) and the standard deviation of the sample means should be $25.77/\sqrt{25} = 5.154$ which was about 5.12. The differences were expected due to the limitation of 1000 sample means used in the example versus the many more times of sample means actually included in the Central Limit Theorem.

Options

Summary statistics:

Column	Mean
Sample1	87.112
Sample2	88.1528
Sample3	86.65
Sample4	86.96
Sample5	87.6052
Sample6	89.2424
Sample7	85.5096
Sample8	96.3964
Sample9	82.7476
Sample10	83.0088
Sample11	82.5332
Sample12	91.782
Sample13	82.4708
Sample14	100.6712
Sample15	91.2336
Sample16	90.402
Sample17	77.9036
Sample18	89.2992
Sample19	88.5212
Sample20	88.8164

Figure 20. Sample means computed from 1000 samples of size 25

Options

Summary statistics:

Column	Mean	Std. dev.
Sample Means	87.120986	5.1228716

Figure 21. Mean and standard deviation of the 1000 sample means

Strengthening statistical concepts through understanding statistics.

a. The applets built into the *StatCrunch* package assisted in developing students' statistical literacy and reasoning: Many applets are available on *StatCrunch*. For example, Simulation on Die Rolling applet illustrates how probability is understood through the Law of Large Numbers, and the Correlation by Eye applet allows students to guess the sample correlation of a data set and to make sense of the correlation between two variables. Two applets used in the course topic of Sampling & Inference on Population Means are described here: Sampling Distribution applet and Confidence Intervals applet. While Sampling Distributions applet is for understanding Central Limit Theorem, Confidence Intervals applet is for understanding the conceptual meaning of confidence level.

    As mentioned in the previous section, the Sampling Distribution applet was used to deliver the concept of sample mean distribution through the aspect of *understanding* statistics. When population distribution follows a normal distribution, sample mean distribution follows a normal distribution regardless of the sample size being as small as 2 (Figure 22), or as large as 100 (Figure 23). However, the larger the sample size is, the smaller the standard error of the sample mean distribution. When population distribution is skewed, sample mean distribution is skewed with a small sample size (Figure 24). However, the shape of the sample mean distribution could be improved and tended to be more symmetric as the sample size increases to at least 25 (Figure 25). The Confidence Intervals applet, on the other hand, provides a clear conceptual understanding about the confidence level used in constructing confidence intervals. Rather than

interpreting a 95% confidence interval as having a 95% chance that the confidence interval captures the true population parameter, a confidence level of 95% means that the probability of capturing the true population parameter is about 95 out of 100. That is, out of a total of 100 confidence intervals constructed from 100 different samples of the same sample size selected randomly from the same population, approximately 95 of the intervals could capture the true population parameter. Through the Confidence Intervals applet simulation, the conceptual understanding of the confidence level became easy to grasp. Figure 26 displays the simulation results that the probability of containing the true population mean out of a total of 5000 confidence intervals was 0.9498, which was approximately the same as the confidence level of 95%.

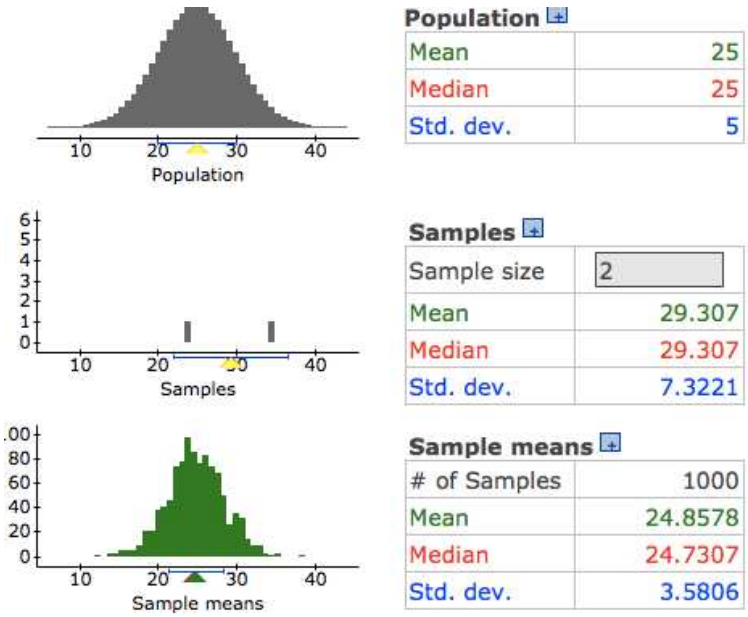


Figure 22. Screenshot of sampling distribution applet for a normal population distribution with n = 2

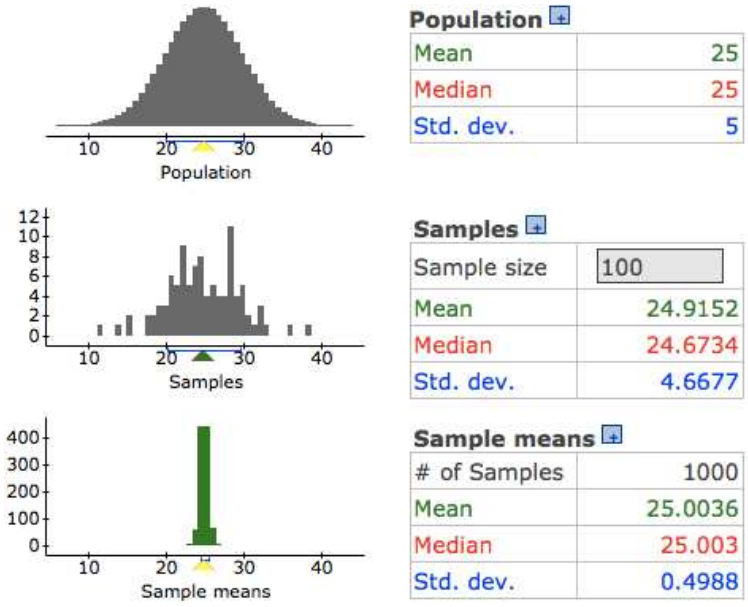


Figure 23. Screenshot of sampling distribution applet for a normal population distribution with n = 100

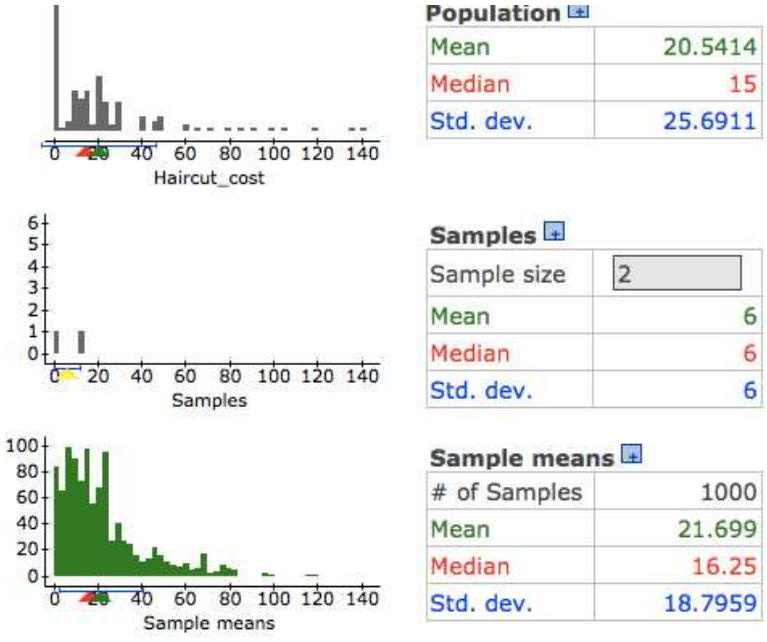


Figure 24. Screenshot of sampling distribution applet for a skewed population distribution with n = 2

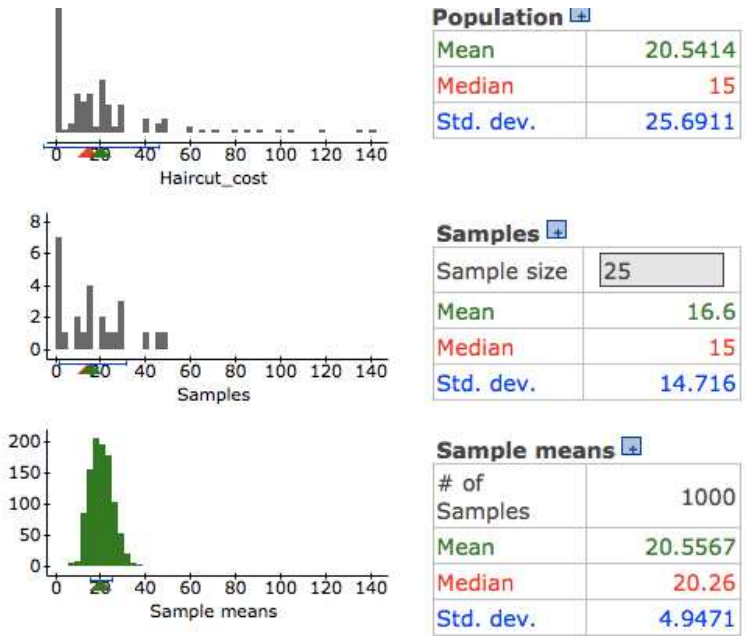


Figure 25. Screenshot of sampling distribution applet for a skewed population distribution with n = 25

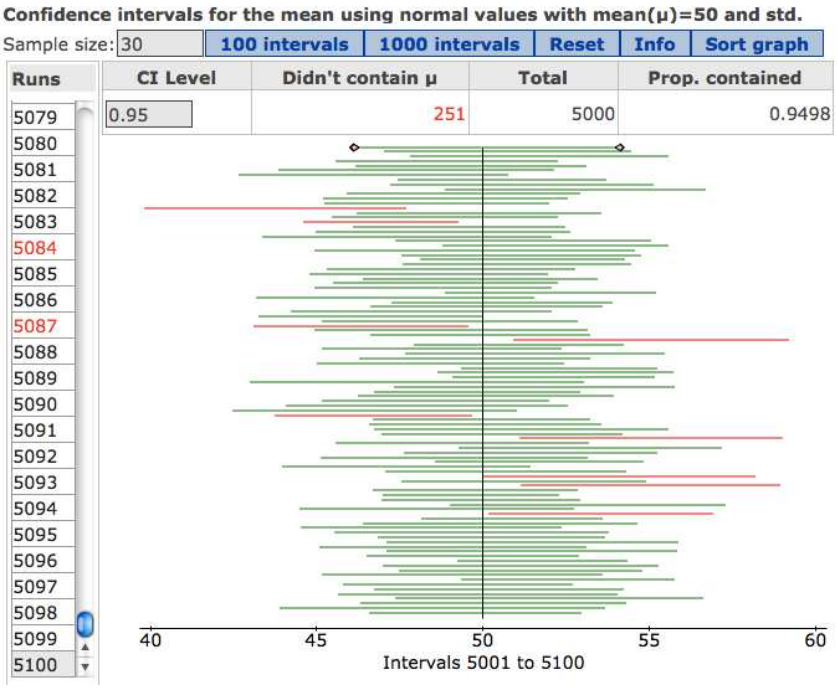


Figure 26. Screenshot of confidence intervals applet

Research Question 3: How does Statistics Instruction Designed According to Merrill's First Principles Improve Teaching and Learning Quality (TALQ) and Develop Statistical Conceptual Understanding?

The course evaluation instrument TALQ survey (Frick et al., 2009) used in the present study evaluated whether Merrill's First Principles of Instruction were implemented in the course design and measured the teaching and learning quality of the course. In particular, the objectively assessed CAOS scores and the level of understanding coding results obtained from content analysis on participants' weekly discussions, topical projects, and interview data were included to support the subjective teaching and learning quality measured by TALQ from students' perspective. Additionally, the development of statistical conceptual understanding is described followed by an overall conclusion.

The implementation of Merrill's First Principles of Instruction.

According to the TALQ survey results, on average, the participants agreed or strongly agreed that the five principles, namely, authentic problems principle, activation principle, demonstration principle, application principle, and implication principle were properly implemented in the course. That is, the participants approved the inclusion of real-world authentic tasks in the instruction, having the opportunity to recall and apply past experiences to the new materials, the incorporation of the demonstration of the skills expected to learn in the course, having the chance to practice the materials learned, and the allowance of the discussion and defense of the materials learned. In addition, the participants agreed or strongly agreed that the Pebble-in-the-Pond approach, or, the

gradual reduce on coaching and feedback approach, was experienced as the learning continued.

Learning and teaching quality.

Participants, in general, agreed or strongly agreed that the overall quality of the course and the instructor were outstanding and considered the class as a great class. They agreed that the technology, including *Etudes* and *StatCrunch*, used in the course helped the participants to learn. The survey also showed that the participants were satisfied with the course and enjoyed learning about the subject matter. Moreover, participants considered themselves as hard-working students in terms of the much effort and time spent on learning the course materials. Not surprisingly, all but one agreed or strongly agreed that they learned a lot in the course. As for the difficulty level of the course, survey results showed that not all the participants surveyed considered this course as the most difficult course they have taken.

Through regression analysis, significant correlations were found among Academic Learning Scale (ALS), Learning Scale (LS), Self-reported course mastery, and objectively assessed CAOS scores. In summary, on average, the more time and effort the surveyed participants reported to spend in the course, the higher agreements on gaining more knowledge from the course and achieving higher-level of self-reported mastery of the course, and the higher objective CAOS scores in the final course assessment. Frick et al. (2010) reported a similar result in their study that when the Academic Learning Scale (ALS) was reported to occur during the learning process, students experienced positive learning results.

Although no significant correlations were found between Merrill's First Principles of Instruction scales and the CAOS score, a significant association between the implementation of Merrill's First Principles of Instruction and participants' level of conceptual understanding was revealed. That is, the effectiveness of the implementation of Merrill's First Principles of Instruction was found when examining the association between the assignment type (weekly discussions and topical projects) and the level of understanding (no understanding, vague understanding, and clear understanding). In particular, implementing Merrill's First Principles of Instruction into the course design when learning the topic of Inferring Population Means was found significantly related to participants' understanding with a significant increase of 13% of clear understanding among the eight participants. Finally, the average level of clear conceptual understanding was shown established and maintained at approximately the same level from during-the-semester-training to the semester-end interviews.

Development of statistical conceptual understanding.

Four purposefully selected students' cognitive development process was qualitatively described in full detail to understand their development of conceptual understanding in terms of statistical literacy, reasoning, and thinking. The content analysis results show that all but one participant improved their statistical conceptual development through the course design. Traditionally, students in introductory statistics courses are challenged with data interpretation. The pre-requisite to the non-calculus based introductory statistics course is intermediate algebra where students are accustomed to working with questions without containing the context, for example, solving the equations by finding the solutions. However, data analysis in statistics focuses

on the interpretation of statistical results. Therefore, the capability of interpreting statistical results using context in non-technical terms in order to communicate with the laymen is vital in learning statistics. In the beginning of the semester, the four selected participants struggled with the inclusion of the context and the meaningful interpretation of the results even when the context was included. However, with continuous training and practicing through demonstration, application, and integration implemented in the course design of the four course topics, satisfactory improvement on the interpretation of statistical results using proper context in non-technical terms could be detected in the four selected students as the semester proceeded.

The issue of having data consciousness prior to statistical analysis posed another challenge for the four selected participants at the start of the semester. Due to the messy nature of the real-world data, one has to develop the consciousness of 'cleaning' the data by excluding the missing data or correcting the incorrectly recorded data. In addition to the data cleanup process, being able to differentiate between qualitative data and quantitative data is vital to avoid selecting an incorrect statistical analysis method. The incorrect statistical analysis invalidates the entire statistical procedure and renders meaningless statistical results. Through the repeated demonstration, application, and integration phases, three of four selected participants successfully developed data consciousness as the learning progressed.

Only one out of the four selected participants effectively developed reasoning and thinking statistically as the learning progressed. The improvement of statistical literacy in regard to statistical results interpretation and data consciousness described above were also observed in the study. However, insufficient understanding of some statistical results

due to the confusion of statistical terminology was shown in all selected participants except one at the semester-end interview results. That is, most of the participants did not overcome the difficulties of fully understanding statistical terminology through the reiterated process designed in the course. This qualitative content analysis finding was supported by the quantitative analysis semester-end interview results that only 29% of the items related to statistical literacy marked as clear understanding comparing with the same 69% of clear understanding rates for the items related to statistical reasoning and thinking. Moreover, the qualitative analysis pinpoints the real cause of the low statistical literacy rate as being the lack of full understanding of statistical terminology.

In summary, when evaluating the course, participants acknowledged the implementation of First Principles course design and responded positively regarding the course as outstanding. Contrary to a general belief that the course of introductory statistics is difficult and boring, not all the participants in the present study considered the course as the most difficult. This result could be an indication that the course design of implementing Merrill's First Principles of Instruction helped some students in learning in a positive way and reduced the difficulty level in the process of learning. A significant association between the implementation of Merrill's First Principles of Instruction and participants' level of conceptual understanding further supported the indication. Furthermore, the overall conceptual understanding was established and maintained at the same level as the course proceeded to the semester end. Taken together, the overall effectiveness of implementing Merrill's First Principles of Instruction into the course design can be concluded as positive. That is, the tertiary-level introductory statistics

course designed with implementation of Merrill's First Principles of Instruction does promote students' conceptual understanding.

Implications

As an original contribution to the field of computing technology in education, the study sought to shed light on instructional design and technology's role in the design and implementation of a blended introductory statistics course at the tertiary level. The results provide guidance to researchers and practitioners who seek instructional design suggestions that incorporate real data, social networking tools, and technologies to improve students' statistical conceptual understanding. Specifically, the study makes the following contributions:

- The study contributes to the field of instructional design through an intensive evaluation of Merrill's First Principles Instruction implemented into a tertiary level introductory statistics course (Merrill, 2009).
- The study validates the efficiency and effectiveness of the instruction when incorporating Merrill's First Principles of Instruction into the instructional design (Merrill, 2009).
- The study confirms the principles (demonstration principle, application principle, task-centered principle, activation principle, and integration principle) promoted by Merrill (2009) as a good starting point in building a common knowledge base for instructional design (Merrill, 2009).
- The study contributes to the field of statistics education at the tertiary level through originating innovated course design of a technology-enhanced learning environment that incorporates real data generated from social networking sites

to engage students in developing conceptual understanding (Brown & Kass, 2009; Gould 2010).

- The study contributes to the field of statistics education by documenting qualitatively the development of the conceptual understanding when learning a blended online introductory statistics course designed with the implementation of Merrill's First Principles of Instruction.
- The study supports the ongoing reform in statistics education in promoting students' conceptual understanding of reasoning and thinking statistically (Garfield, Hogg, Schau, & Whittinghill, 2002).

Although retention rates at the community college studied and the statistics course, in particular, are relatively low due to the population it serves (i.e., students with disadvantaged socioeconomic background), it is important to address the dropout rate in this course in order to provide a clearer picture of the context within which to consider the implementation of this course design in future instances. As noted in Chapters 3 and 4, ten students out of an initial 40 enrolled students completed the course and received a course grade. This ratio translates to a dropout rate of 75%. To understand if the implementation of the course design had an impact on the dropout rate, a significance test comparing the dropout rate of the studied class (75%) with the typical dropout rate of hybrid statistics classes (66%) offered in the studied college was conducted. The result of the test was insignificant with a *p*-value of 0.2295 indicating that incorporating Merrill's First Principles of Instruction into the course design did not have the direct impact on the dropout rate. Furthermore, from those who did not complete the course, an overwhelming majority (78%) dropped within the first month. After conferring with the school's

academic counselor, it was determined that many students “shop” courses to find an easy-to-pass statistics course. The course began with 40 students but by the fifth week, only 15 students completed the online discussions and the first project. Of the 25 students who dropped the course, nine (36%) never participated in the course and the remaining 16 students (64%) were dropped by the fifth week in accordance with the syllabus’ participation policy (stating that student who fails to participate in online discussions for two weeks will be dropped from the course). After data analyses were completed on the eight students who actively completed the course, five students who dropped out of the course and two students who became inactive toward the end of the course were contacted via email to find out why they dropped or became inactive, and what their perceptions were of the course design. Given the explanation for early dropouts within the first four weeks of the course, questions were targeted for the seven of the 15 students who officially dropped out or became inactive later in the semester. The following two questions were sent to the students:

1) Why did you drop the class/become inactive at the end of the semester?
2) What was your experience with the course design?

Responses were varied from those five responding to the post-course survey questions. One student reported that he/she took too many credits and could not handle the workload required from the course. Another student, who was doing well, dropped the course because he/she had a personal issue, which caused him/her to miss the assignments for one week and therefore felt he/she could not catch up. Another student who was doing well in the discussions and project reported that he/she dropped the course because he/she later found out that the course was not required for him/her to

transfer. The two inactive students reported that they were failing the course yet passed the deadline of dropping the course. So, they stopped participating the discussions. Among those who responded to the post-course survey questions, four students attributed their dropping the course to their lack of time management and self-discipline.

Four out of the five made comments regarding the course design. All four students reported a positive learning experience. One student said that although it required a lot of work of reading and discussing online, the repetitive nature of learning the course materials helped to reinforce the concepts.

Merrill's First Principles of Instruction was not implemented into the course design until the second week. Although not directly impacted with the dropout rate, the course designed with First Principles of Instruction requires effort and hard work, as does the development of statistical reasoning and thinking in general. Students took the course to fulfill their transfer requirements. It is possible that the rigor of the course design coupled with the inherent difficulty of the course content presented a perceived difficulty level that was too much for the non-traditional college students to handle. To alleviate the potential stress caused by the perceived high difficulty level, perhaps Merrill's First Principles of Instruction could be implemented on fewer course topics or delayed until the students have learned the basics in the beginning of the course. By gradually increasing the workload, it might "save" the students from dropping and help them to adapt into this new strategy of learning through conceptual understanding.

Recommendations

This research describes an embedded single-case study of how learners taking a tertiary level introductory statistics course designed by applying Merrill's First Principles

of Instruction with emphases on technology and real data developed their statistical literacy, reasoning, and thinking skills. Although results from quantitative and qualitative content analyses reveal that the course design is effective in developing students' conceptual understanding, one cannot establish the analytic generalization from the results of a single-case study. A multiple-case study design is required to generalize the effectiveness of the course design (Yin, 2009). Therefore, replication of the study in different cases (classes) of the same setting is recommended.

The instructional design developed in the study was tested in a small-scale class setting. Merrill (2009) encouraged researchers from various academic settings with different disciplines and fields verify the Principles of Instruction to wide variety of audiences with various cultural backgrounds. It is, therefore, recommended for examining the efficiency and effectiveness of the course design in various disciplines at different and large-scale settings worldwide.

Overall, the study discloses a course design positively encouraging the development of learners' conceptual understanding. However, students' statistical literacy, specifically, the understanding of statistical terminology did not develop to a satisfactory level as expected. Terminology involves rote memory of the statistical terms. While the emphasis of statistics learning is on its conceptual understanding, there is a fundamental need to clearly identify statistical terms when communicating with each other and to aid the learning of the more complex course materials as the learning continues. Merrill's First Principles of Instruction calls for a *structure* for building up the new knowledge by adding relevant and accurate information and deleting irrelevant and incorrect information as the learning proceeds. The *structure* is served as the basis for guidance,

coaching, and reflection during the demonstration, application, and integration phase, respectively (Merrill, 2009). To effectively achieve the learning results, Merrill suggests a gradual decreasing on coaching and guidance while increasing on the complexity of the whole task. While this is shown effective in grasping the conceptual understanding, on the issue of statistical terminology, however, the results were unsatisfactory compared with the standard achievement. To assist the learners in building up and adjusting the *structure* for the very many similar terms yet very different in meanings and purposes (e.g. sample distribution vs. sampling distribution; a sample mean vs. sample mean distribution), frequent assessment on the statistical terminology alone during the demonstration, application, and integration phases could be effective in assisting learners to sort out and adjust the *structure* for the building of statistical terminology when more terms are introduced and accumulated. Further research is recommended in modifying the course design by including frequent assessment to promote students' deep understanding and reducing the confusion of statistical terminology.

Last, even though the course design assists learners' development of conceptual understanding in general, how much can the students remember what they have learned after they leave the course? The integration principle of Merrill's First Principles of Instruction assures the retention of the new skills when they are integrated with the existing knowledge through reflecting upon, defending via peer critique, and finding opportunities for personal use. Even when not used immediately, a proper training of the integration shortens the relearning time of the skills (Merrill, 2009). Future studies on retention, transfer of learning to topics outside the classroom, and problem solving ability of those students who successfully completed the course are also recommended.

Summary

Chapter one introduced Merrill's (2002) First Principles of Instruction, including, problem-centered, activation, demonstration, application, and integration. An explanation of how these principles of instruction accommodate the six recommendations suggested in the GAISE Project (Guidelines for Assessment and Instruction in Statistics Education) (American Statistical Association, 2005) of teaching introductory statistics at the tertiary level was provided. These six recommendations include: emphasizing statistical literacy and develop statistical thinking, using real data, stressing conceptual understanding rather than mere knowledge of procedures, fostering active learning in the classroom, using technology for developing concepts and analyzing data, and using assessments to improve and evaluate student learning. The goal was to examine how an innovative pedagogical instruction designed following Merrill's First Principles of Instruction facilitated the development of tertiary-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. The following three research questions guided the investigation: 1) How do Merrill's First Principles of Instruction guide the development of an introductory, technology-enhanced, statistics course? 2) How can *StatCrunch*, a web-based social data analysis site, be used to support meaningful learning? 3) How does statistics instruction designed according to Merrill's First Principles improve teaching and learning quality (TALQ) and develop statistical conceptual understanding? The relevance and significance derived from the need to document real-world data exploration experience for the learners, the effects of utilizing social networking sites in support of the teaching, and the impacts of First Principles of Instruction on learners' ability to think statistically were detailed. Chapter

two presented an overview of the research literature informing Merrill's First Principles of Instruction supported in course design, the strategies applied in the instructional design when teaching introductory statistics at the tertiary level, and a review on social networking services employed in academics.

Chapter three detailed the forming of a descriptive embedded single-case study design for the purpose of being capable of qualitatively describing what happened to students' cognitive development when learning tertiary level introductory statistics. Specifically, the case included the students enrolled in one section of a blended tertiary level introductory statistics course at a two-year community college in Greater Los Angeles area in Spring 2013 for duration of one semester. The teaching and learning quality (TALQ) survey was embedded in the case study design to quantitatively evaluate the implementation of Merrill's First Principles of Instruction. Four sources of evidence were used for data collection: postings from the online discussion forum, an end-of-course comprehensive assessment (CAOS), open-ended interviews, and the TALQ (teaching and learning quality) survey. Procedures of quantitative and qualitative data analyses were described. In particular, detailed steps of performing qualitative content analysis on online postings and interview data were depicted. The assurance of the quality was also discussed through the description of construct validity, external validity, and reliability.

Chapter four presented quantitative data analysis results of participants' perception of learning and teaching quality supported by objective assessment results. Data collected from the final eight students who completed the entire course work were used for analysis. Results revealed that on average, students who reported spending more time and

effort on studying and preparing for the course perceived gaining more knowledge from the course with higher level of self-reported mastery of the course, and achieved higher objective CAOS scores in the final course assessment. Furthermore, participants' level of clear understanding progressed from the time when participating in online discussions to the time when topical projects were submitted. Finally, the quantitative results showed that the level of conceptual understanding had been established during the semester training and was maintained at the similar level at the semester-end interviews. A detailed qualitative description of cognitive development toward conceptual understanding in terms of statistical literacy, reasoning, and thinking was demonstrated through a selected purposeful sample of participants.

Chapter five concluded the study by detailing how the course was designed based on the framework of Merrill's First Principles of Instruction. Specifically, the course design of the weekly module of Part II – Significance Test for the Population Mean of the course topic of Sampling & Inferences on Population Means delivered in the tenth week of the semester was described in greater depth. The usage of *StatCrunch* in supporting meaningful learning in terms of strengthening statistical concepts through doing statistics and understanding statistics was next illustrated. Third, the improvement of teaching and learning quality and the development of statistical conceptual understanding of the statistics instruction designed according to First Principles were summarized. The contributions the study makes to the fields of instructional design and statistics education were described. Finally, recommendations for further research were discussed.

This research detailed how a blended tertiary-level introductory statistics course was designed based on First Principles of Instruction with an emphasis on implementing

real data and technology. Results from both quantitative and qualitative data analyses indicate that the course designed following Merrill's First Principles of Instruction contributes to a positive overall effectiveness of promoting students' conceptual understanding in terms of literacy, reasoning, and thinking statistically. However, students' statistical literacy, specifically, the understanding of statistical terminology did not develop to a satisfactory level as expected.

Appendix A

Teaching and Learning Quality (TALQ) Survey

Teaching and Learning Quality (TALQ) Research Study

Directions: Please complete this form to evaluate the course Math 227-4950: Introductory Statistics. This survey is divided into 4 parts. There are 48 questions where you circle your answer. It takes about 10 minutes.

Please answer the following questions about this class:

a. I would rate this class as (Circle one):

   10: Really great (Outstanding)
   9
   8
   7
   6
   5: About average
   4
   3
   2
   1: Really awful (Poor)

b. In this course, I expect to receive a grade of (Circle one):

   A
   B
   C
   D
   F
   Don't Know

c. With respect to achievement of objectives of this course, I consider myself a:

   10: High Master
   9
   8
   7
   6
   5: Medium Master
   4
   3
   2
   1: Low Master

Proceed to Part 2

Teaching and Learning Quality (TALQ) Study: Part 2

Directions: For each statement below, rate how much you agree/disagree with the statement where 5 indicates “Strongly agree”, 4 indicates “Agree”, 3 indicates “Neutral”, 2 indicates “Disagree”, and 1 indicates “Strongly disagree”. Please circle a number for each statement.

Note: In the items below, *authentic problems* or *authentic tasks* are meaningful learning activities that involved real-world data.

1. I did not do very well on most of the tasks in this course, according to my instructor’s judgment of the quality of my work.

   5 4 3 2 1

2. I am very satisfied with how my instructor taught this class.

   5 4 3 2 1

3. I performed a series of increasingly complex authentic tasks in this course.

   5 4 3 2 1

4. Compared to what I knew before I took this course, I learned a lot.

   5 4 3 2 1

5. My instructor demonstrated skills I was expected to learn in this course.

   5 4 3 2 1

6. I am dissatisfied with this course.

   5 4 3 2 1

7. My instructor detected and corrected errors I was making when solving problems, doing learning tasks or completing assignments.

   5 4 3 2 1

8. Overall, I would rate the quality of this course as outstanding.

   5 4 3 2 1

9. I engaged in experiences that subsequently helped me learn ideas or skills that were new and unfamiliar to me.

   5 4 3 2 1

10. I learned a lot in this course.

    5 4 3 2 1

11. I had opportunities in this course to explore how I could personally use what I have learned.

    5 4 3 2 1

12. I frequently did very good work on projects, assignments, problems and/or learning activities for this course.

    5 4 3 2 1

13. This course is one of the most difficult I have taken.

    5 4 3 2 1

14. I spent a lot of time doing tasks, projects and/or assignments, and my instructor judged my work as high quality.

    5 4 3 2 1

15. Technology used in this course (online homework, online discussion platform, StatCrunch) helped me to learn instead of distracting me.

    5 4 3 2 1

Proceed to Part 3

Teaching and Learning Quality (TALQ) Study: Part 3

Directions: For each statement below, rate how much you agree/disagree with the statement where 5 indicates “Strongly agree”, 4 indicates “Agree”, 3 indicates “Neutral”, 2 indicates “Disagree”, and 1 indicates “Strongly disagree”. Please circle a number for each statement.

16. Overall, I would rate this instructor as outstanding.

    5 4 3 2 1

17. My instructor gave examples and counter-examples of concepts that I was expected to learn.

    5 4 3 2 1

18. This course increased my interest in the subject matter.

    5 4 3 2 1

19. My instructor directly compared problems or tasks that we did, so that I could see how they were similar or different.

    5 4 3 2 1

20. This course was a waste of time and money.

    5 4 3 2 1

21. In this course I was able to recall, describe or apply my past experience so that I could connect it to what I was expected to learn.

    5 4 3 2 1

22. Looking back to when this course began, I have made a big improvement in my skills and knowledge in this subject.

    5 4 3 2 1

23. My instructor gradually reduced coaching or feedback as my learning or performance improved during this course.

    5 4 3 2 1

24. I put a great deal of effort and time into this course, and it has paid off – I believe that I have done very well overall.

    5 4 3 2 1

25. I solved authentic problems or completed authentic tasks in this course.

    5 4 3 2 1

26. Opportunities to practice what I learned during this course (e.g., assignments, class activities, solving problems) were not consistent with how I was formally evaluated for my grade.

    5 4 3 2 1

27. I learned very little in this course.

    5 4 3 2 1

28. I see how I can apply what I learned in this course to real life situations.

    5 4 3 2 1

29. I did a minimum amount of work and made little effort in this course.

    5 4 3 2 1

30. My instructor provided a learning structure that helped me to mentally organize new knowledge and skills.

    5 4 3 2 1

Proceed to Part 4

Teaching and Learning Quality (TALQ) Study: Part 4

Directions: For each statement below, rate how much you agree/disagree with the statement where 5 indicates “Strongly agree”, 4 indicates “Agree”, 3 indicates “Neutral”, 2 indicates “Disagree”, and 1 indicates “Strongly disagree”. Please circle a number for each statement.

31. In this course I solved a variety of authentic problems that were organized from simple to complex.

    5 4 3 2 1

32. I did not learn much as a result of taking this course.

    5 4 3 2 1

33. Assignments, tasks, or problems I did in this course are helping me to develop the skills of thinking statistically.

    5 4 3 2 1

34. I was able to publicly demonstrate to others what I learned in this course.

    5 4 3 2 1

35. My instructor did not demonstrate skills I was expected to learn.

    5 4 3 2 1

36. I had opportunities to practice to try out what I learned in this course.

    5 4 3 2 1

37. In this course I was able to reflect on, discuss with others, and defend what I learned.

    5 4 3 2 1

38. Overall, I would recommend this instructor to others.

    5 4 3 2 1

39. In this course I was able to connect my past experience to new ideas and skills I was learning.

5 4 3 2 1

40. I enjoyed learning about this subject matter.

5 4 3 2 1

41. In this course I was not able to draw upon my past experience nor relate it to new things I was learning.

5 4 3 2 1

42. My course instructor gave me personal feedback or appropriate coaching on what I was trying to learn.

5 4 3 2 1

43. My instructor provided alternative ways of understanding the same ideas or skills.

5 4 3 2 1

44. I do not expect to apply what I learned in this course to my chosen profession or field of work.

5 4 3 2 1

45. I am very satisfied with this course.

5 4 3 2 1

You're done. Thank you for your participation.

Appendix B

Informed Consent Document

Consent Form for Participation in the Research Study Entitled: *Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment*

Funding Source: None

IRB protocol # 10311218Exp.

Principal investigator
Wendy Miao, M.A.
9000 Overland Ave.
Culver City, CA 90230
(310) 287-4200

Co-investigator
Martha Snyder, Ph.D.
3301 College Avenue
Fort Lauderdale, FL 33314
(954) 262-2074

For questions/concerns about your research rights, contact:

Human Research Oversight Board (Institutional Review Board or IRB)
Nova Southeastern University
(954) 262-5369/Toll Free: 866-499-0790
IRB@nsu.nova.edu

Site Information
West Los Angeles College
Mathematics Department
9000 Overland Ave.
Culver City, CA 90230

What is the study about?
You are invited to participate in a research study. The goal of this study is to understand how the course design based on First Principles of Instruction can facilitate college-level students' conceptual understanding when learning introductory statistics in a technology-enhanced learning environment. This research is important to shed light on instructional design and technology's role in the design and implementation of a blended introduction to statistics course at the college level.

Why are you asking me?
We are inviting you to participate because you are currently enrolling in a blended online introductory statistics course at a higher education institution. There will be between 30 and 40 participants in this research study.

What will I be doing if I agree to be in the study?
You will be interviewed by the researcher and facilitator, Ms. Wendy Miao. You will be asked to describe an appropriate statistical analysis procedure when investigating a real-life scenario. You will answer a 48-question survey to evaluate the learning and teaching of the course. The survey should take you no more than 15 minutes to complete and the interview will last no more than 10 minutes.

Is there any audio or video recording?
This research project will include audio recording of the interview. This audio recording will be available to the researcher, Ms. Wendy Miao, the Institutional Review Board (IRB), and the dissertation chair, Dr. Martha Snyder. The recording will be transcribed by Ms. Wendy Miao and the digital audio file will be kept securely in Ms. Wendy Miao's office in a locked drawer. The recording will be kept for 36 months from the end of the study. The recording will be destroyed after that time by deleting the digital file. Because your voice will be potentially identifiable by anyone who hears the recording, your confidentiality for things you say on the recording cannot be guaranteed although the researcher will try to limit access to the recording as described in this paragraph.

What are the dangers to me?
Risks to you are minimal, meaning they are not thought to be greater than other risks you experience every day. Being recorded means that confidentiality cannot be promised. The possible risk of losing confidentiality could occur during the entire period of study when data from online postings, online discussions, online peer critiques, final assessment, survey, and interviews are collected. If you have questions about the research, your research rights, or if you experience an injury because of the research please contact Ms. Miao at (310) 287-4200. You may also contact the IRB at the numbers indicated above with questions about your research rights.

Are there any benefits for taking part in this research study?
There are no direct benefits for participating in this study.

Will I get paid for being in the study? Will it cost me anything?
There are no costs to you or payments made for participating in this study.

How will you keep my information private?
The survey on course evaluation will be kept away from the course facilitator, Ms. Wendy Miao, until your course grade has been officially submitted. The transcripts of online postings, the interview data, final assessment results, and survey results will be linked for a better understanding of your conceptual learning. All the data will be linked through a coding key list, a list consisting of student ID's along with the assigned pseudonyms. This coding key list will be securely stored separately from all other data in a sealed envelope in a locked drawer in Ms. Miao's office. All the data collected from you along with the coding key list will be destroyed 36 months after the study ends. All information obtained in this study is strictly confidential unless disclosure is required by law. The IRB, regulatory agencies, or Dr. Martha Snyder may review research records.

Use of Student/Academic Information:
Your postings from online discussion forum including assignment postings and critique as well as your final assessment results will be used to understand how the course design based on First Principles of Instruction can affect college-level students' conceptual understanding.

What if I do not want to participate or I want to leave the study?
You have the right to leave this study at any time or refuse to participate. If you do decide to leave or you decide not to participate, you will not experience any penalty. If you choose to withdraw, any information collected about you before the date you leave the study will be kept in the research records for 36 months from the conclusion of the study and may be used as a part of the research.

Other Considerations:
If the researcher learns anything that might change your mind about being involved, you will be informed of this information.

Voluntary Consent by Participant:
By signing below, you indicate that

- this study has been explained to you
- you have read this document or it has been read to you
- your questions about this research study have been answered
- you have been told that you may ask the researchers any study related questions in the future or contact them in the vent of a research-related injury
- you have been told that you may ask Institutional Review Board (IRB) personnel questions about your study rights
- you are entitled to a copy of this form after you have read and signed it
  you voluntarily agree to participate in the study: *"Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment"*

Participant's Signature: _____ Date: _____

Participant's Name: _____ Date: _____

Signature of Person Obtaining Consent: _____

Date: _____

Appendix C

Permission to use Comprehensive Assessment of Outcomes in a first Statistics Course (CAOS) test

From: Robert delMas [delma001@umn.edu]
Sent: Tuesday, September 25, 2012 5:12 PM
To: MIAO_WENDY
Subject: Re: Seeking permission of using CAOS as an instrument in my study

Dear Wendy:

Thank you for asking for permission to use the CAOS test in your research project. I am happy to grant you permission, especially since using the CAOS test in educational research was one of the main purposes for developing the test.

I see that you registered to access and administer the ARTIST online tests, which includes CAOS, back in 2005. If you are intending to have the research participants take CAOS through the ARTIST online testing website (and I hope that you are), then I can provide you with data files of the participants' individual responses once they have completed the CAOS test if you provide me with evidence of Human Subjects IRB approval from your institution.

And please let me know if you have additional questions.

Best regards,

Bob delMas
****
Robert C. delMas, Ph.D.
Associate Professor
Quantitative Methods in Education
Director, APECS Minor
Department of Educational Psychology

University of Minnesota
250 Education Sciences Building
56 East River Road
Minneapolis, MN 55455

Phone: (612) 625-2076
Fax: (612) 624-8241

Appendix D

Interview Protocol

The following is an example of the scenario that will be given during the open-ended interview.

Instructions: 1). Please think loudly throughout the interview.
2). To avoid bias, no further explanation of the given scenario and questions will be provided.
3). You may be asked by the interviewer for further clarification of your responses.

Scenario: Researchers claim that women speak significantly more words per day than men. One estimate is that a woman uses about 20,000 words per day while a man uses about 7,000. (Adapted from Moore et al., 2013)

Part 1. Describe the statistical analysis process you consider as appropriate to investigate such claims.

Part 2. To investigate such claims, one study used a special device to record the conversations of male and female university students over a four-day period. From these recordings, the daily word count of the 20 men in the study was determined. The following is the statistical analysis printout from StatCrunch. According to the results, what can you conclude about the claim that the mean number of words per day of men at this university differs from 7,000?

Hypothesis test results:

μ : mean of Variable

$H_0 : \mu = 7000$

$H_A : \mu \neq 7000$

Variable	Sample Mean	Std. Err.	DF	T-Stat	P-value
Word Count	12866.7	1865.4335	19	3.1449525	0.0053

Appendix E

Teaching and Learning Quality (TALQ) Survey Items Arranged by TALQ Scales

Scale	Item Number*/Item
TALQ Scales	
Academic Learning Scale	
	1- I did not do very well on most of the tasks in this course, according to my instructor's judgment of the quality of my work.
	12 I frequently did very good work on projects, assignments, problems and/or learning activities for this course.
	14 I spent a lot of time doing tasks, projects and/or assignments, and my instructor judged my work as high quality.
	24 I put a great deal of effort and time into this course, and it has paid off – I believe that I have done very well overall.
	29- I did a minimum amount of work and made little effort in this course.
Learning Scale	
	4 Compared to what I knew before I took this course, I learned a lot.
	10 I learned a lot in this course.
	22 Looking back to when this course began, I have made a big improvement in my skills and knowledge in this subject.
	27- I learned very little in this course.
	32- I did not learn much as a result of taking this course.

* Item numbers followed by a negative sign are negatively worded.

Scale	Item Number*/Item
Learner Satisfaction Scale	
	2 I am very satisfied with how my instructor taught this class.
	6- I am dissatisfied with this course.
	20- This course was a waste of time and money.
	45 I am very satisfied with this course.
First Principles of Instruction – Authentic Problems Scale	
	3 I performed a series of increasingly complex authentic tasks in this course.
	23 My instructor directly compared problems or tasks that we did, so that I could see how they were similar or different.
	25 I solved authentic problems or completed authentic tasks in this course.
	31 In this course I solved a variety of authentic problems that were organized from simple to complex.
	33 Assignments, tasks, or problems I did in this course are helping me to develop the skills of thinking statistically.

Scale	Item Number*/Item
First Principles of Instruction – Activation Scale	
	9 I engaged in experiences that subsequently helped me learn ideas or skills that were new and unfamiliar to me.
	21 In this course I was able to recall, describe or apply my past experience so that I could connect it to what I was expected to learn.
	30 My instructor provided a learning structure that helped me to mentally organize new knowledge and skills.
	39 In this course I was able to connect my past experience to new ideas and skills I was learning.
	41- In this course I was not able to draw upon my past experience nor relate it to new things I was learning.
First Principles of Instruction – Demonstration Scale	
	5 My instructor demonstrated skills I was expected to learn in this course.
	17 My instructor gave examples and counter-examples of concepts that I was expected to learn
	35- My instructor did not demonstrate skills I was expected to learn.
	43 My instructor provided alternative ways of understanding the same ideas or skills.

Scale	Item Number*/Item
First Principles of Instruction – Application Scale	7 My instructor detected and corrected errors I was making when solving problems, doing learning tasks or completing assignments.
	36 I had opportunities to practice to try out what I learned in this course.
	42 My course instructor gave me personal feedback or appropriate coaching on what I was trying to learn.
First Principles of Instruction – Integration	11 I had opportunities in this course to explore how I could personally use what I have learned.
	28 I see how I can apply what I learned in this course to real life situations.
	34 I was able to publicly demonstrate to others what I learned in this course.
	37 In this course I was able to reflect on, discuss with others, and defend what I learned.
	44- I do not expect to apply what I learned in this course to my chosen profession or field of work.
First Principles of Instruction – Pebble-in-the-Pound Approach	23 My instructor gradually reduced coaching or feedback as my learning or performance improved during this course.

Scale	Item Number*/Item
Global Rating Items	
	8 Overall, I would rate the quality of this course as outstanding.
	16 Overall, I would rate this instructor as outstanding.
	38 Overall, I would recommend this instructor to others.
Miscellaneous Items	
	13 This course is one of the most difficult I have taken.
	15 Technology used in this course (online homework, online discussion platform, StatCrunch) helped me to learn instead of distracting me
	18 This course increased my interest in the subject matter.
	26- Opportunities to practice what I learned during this course (e.g., assignments, class activities, solving problems) were not consistent with how I was formally evaluated for my grade.
	40 I enjoyed learning about this subject matter.

Appendix F

Grading Sheet for Coding Descriptive Statistics

Grading Sheet for Coding Descriptive Statistics

Respondent's pseudonym: _____

Descriptive Statistics – Qualitative Data Set

W2-1			
Center (**Typical outcomes**)	None	Vague	Clear
Variability	None	Vague	Clear
Distribution	None	Vague	Clear
Project, Part I			
Center (**Typical outcomes**)	None	Vague	Clear
Variability	None	Vague	Clear
Distribution	None	Vague	Clear

Descriptive Statistics -- Quantitative data sets:

W3-2 (Graphical display)			
Shape	None	Vague	Clear
Number of mounds	None	Vague	Clear
Unusually/ extreme values, if any	N/A None	Vague	Clear
W3-3 (Numerical summary)			
Center:	None	Vague	Clear
Variability:	None	Vague	Clear
Unusual/Extreme Values, if any	N/A None	Vague	Clear
Project, Part II (Graphical display)			
Shape	None	Vague	Clear
Number of mounds	None	Vague	Clear
Unusually/ extreme values, if any	N/A None	Vague	Clear
Project, Part II (Numerical summary)			
Center:	None	Vague	Clear
Variability:	None	Vague	Clear
Unusual/Extreme Values, if any	N/A None	Vague	Clear

Appendix G

Nova Southeastern University IRB Approval

MEMORANDUM

To: Wendy Miao, M.A.
Graduate School of Computer and Information Sciences

From: Ana I. Fins, Ph.D. JD For AF
Chair, Institutional Review Board

Date: December 18, 2012

Re: *Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment* – Research Protocol No. 10311218Exp.

I have reviewed the revisions to the above-referenced research protocol by an expedited procedure. On behalf of the Institutional Review Board of Nova Southeastern University, *Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment* is approved in keeping with expedited review categories #6 and #7. Your study is approved on **December 13, 2012** and is approved until **December 12, 2013**. You are required to submit for continuing review by **November 12, 2013**. As principal investigator, you must adhere to the following requirements:

1) CONSENT: You must use the stamped (dated consent forms) attached when consenting subjects. The consent forms must indicate the approval and its date. The forms must be administered in such a manner that they are clearly understood by the subjects. The subjects must be given a copy of the signed consent document, and a copy must be placed with the subjects' confidential chart/file.

2) ADVERSE EVENTS/UNANTICIPATED PROBLEMS: The principal investigator is required to notify the IRB chair of any adverse reactions that may develop as a result of this study. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g., procedures, consent forms, investigators, etc.) must be approved by the IRB prior to implementation.

4) CONTINUING REVIEWS: A continuing review (progress report) must be submitted by the continuing review date noted above. Please see the IRB web site for continuing review information.

5) FINAL REPORT: You are required to notify the IRB Office within 30 days of the conclusion of the research that the study has ended via the IRB Closing Report form.

The NSU IRB is in compliance with the requirements for the protection of human subjects prescribed in Part 46 of Title 45 of the Code of Federal Regulations (45 CFR 46) revised June 18, 1991.

Cc: Dr. Ling Wang
Dr. Martha M. Snyder
Ms. Jennifer Dillon

Institutional Review Board
3301 College Avenue • Fort Lauderdale, Florida 33314-7796
(954) 262-5369 • Fax: (954) 262-3977 • Email: *irb@nsu.nova.edu* • Web site: *www.nova.edu/irb*

Appendix H

West Los Angeles College Approval

West LA College

An Accredited California Community College

September 27, 2012

Dear Ms. Miao,

Your submission of the research study entitled "Designing for Statistical Reasoning and Thinking in a Technology-Enhanced Learning Environment" has been reviewed and granted permission to be conducted in Spring 2013 within the framework of your Statistics 227 hybrid class. You may proceed with your study as described to the College. As a principal investigator, you must adhere to the following requirements:

1) CONSENT: If recruitment procedures include consent forms, these must be obtained in such a manner that they are clearly understood by the subjects and process affords subjects the opportunity to ask questions, obtain detailed answers from those directly involved in the research, and have sufficient time to consider their participation after they have been provided this information. The subjects must be given a copy of the signed consent document, and a copy must be placed in a secure files separate from de-identified participant information. Record of informed consent must be retained for a minimum of three years from the conclusion of the study.

2) ADVERSE REACTIONS: The principal investigator is required to notify the College of any adverse reactions or unanticipated events that may develop as a result of this study. Reactions or events may include, but are not limited to, injury, depression as a result of participation in the study, life-threatening situation, death, or loss of confidentiality anonymity of subject. Approval may be withdrawn if the problem is serious.

3) AMENDMENTS: Any changes in the study (e.g. procedures, number or types of subjects, consent forms, investigators, etc.) must be approved by the College prior to implementation. Please be advised that changes in a study may require further review depending on the nature of the change. Please contact College with any questions regarding amendments or changes to your study.

We look forward to the completion of your work and the sharing of your findings with the mathematics faculty at West Los Angeles College.

Sincerely,

Judith-Ann Friedman

Dr. Judith-Ann Friedman, Dean
Academic Affairs
General Education and Transfer

9000 Overland Avenue, Culver City, CA 90230
T. (310) 287-4200 | F. (310) 841-0396 | www.wlac.edu

Appendix I

Grading Sheet for Coding Interview Data

Grading Sheet for Coding Interview Data

Respondent's pseudonym: _____

Statistical Literacy:

Data consciousness	N/A	Weak	Moderate	Clear
Statistical concepts	N/A	Weak	Moderate	Clear
Statistical terminology	N/A	Weak	Moderate	Clear
Data collection	N/A	Weak	Moderate	Clear
Generating descriptive statistics	N/A	Weak	Moderate	Clear
Interpretation/communication in layman's terms	N/A	Weak	Moderate	Clear

Statistical Reasoning:

Understanding process	N/A	Weak	Moderate	Clear
Being able to interpret the statistical results	N/A	Weak	Moderate	Clear

Statistical Thinking:

Being able to view the entire statistical process	N/A	Weak	Moderate	Clear
Knowing how/what to investigate through the context	N/A	Weak	Moderate	Clear

---

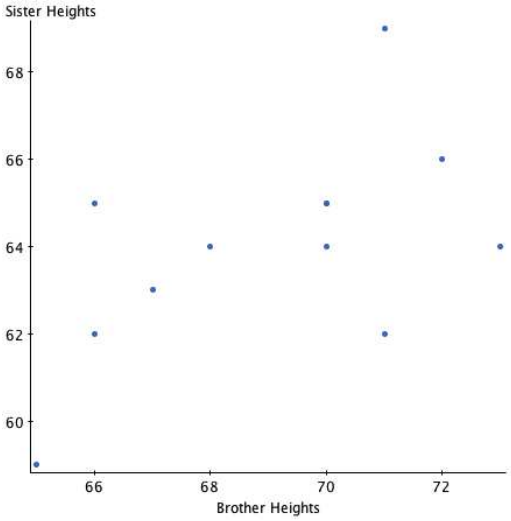
Appendix J

Amelia’s Interview Question

Scenario: How strongly do physical characteristics of sisters and brothers correlate? Heights (in inches) of twelve adult pairs were recorded for analysis. (Adapted from Moore et al, 2013)

Part 1. Describe in words in details the statistical analysis process you consider as appropriate to answer the question. Clearly explain why you choose this statistical analysis process to investigate the question.

Part 2. Data on heights were analyzed using *StatCrunch* and the statistical analysis results are displayed below.



Simple linear regression results:
Dependent Variable: Sister Heights
Independent Variable: Brother Heights
Sister Heights = 28.036707 + 0.52057844 Brother Heights
Sample size: 12
R (correlation coefficient) = 0.5546
R-sq = 0.30761454

Answer the following questions according to the *StatCrunch* analysis results:

1. How strongly do brothers' heights correlate to sisters' heights? Clearly explain how you come up with your conclusion.

2. Damien is 70 inches tall. He wants to predict his sister Tonya's height using the regression model. Do you expect the prediction to be very accurate? Clearly explain why or why not.

Appendix K

Charlie’s Interview Question

Scenario: Do online male daters overstate their heights in online dating profiles? A researcher wants to investigate if the online male daters report their heights in online dating profiles more than their actual heights. (Adapted from Peck, 2014)

Part 1. Describe in words in details the statistical analysis process you consider as the most appropriate to answer the researcher's question. Clearly explain why you choose this statistical analysis process to investigate the question.

Part 2. Forty men with online dating profiles agreed to participate in the study. Each participant's height (in inches) was measured and the height given in that person's online profile was also recorded.

A 95% confidence interval on mean difference of heights between the heights reported in online dating profiles and the actual heights is found to be (0.31, 0.83) with a sample mean difference in height of 0.57 inches and sample standard deviation of difference in height of 0.81 inches.

Answer the following questions according to the *StatCrunch* analysis results:

1. Is there convincing evidence that, on average, male online daters overstate their height in online dating profiles? Report all the conclusions you can draw from the confidence interval results in context. Clearly explain how you get your conclusions.

27. Can the researcher generalize his conclusion to all the online male daters? Justify your answer in details.

Appendix L

Harry's Interview Question

Scenario: A study was conducted to determine if subjects with preexisting cardiovascular symptoms were at an increased risk of cardiovascular events while taking subitramine, an appetite suppressant, comparing with those who took placebo. The primary outcome measured was the occurrence of any of the following events: nonfatal myocardial infarction or stroke, resuscitation after cardiac arrest, or cardiovascular death. (Adapted from Moore et al., 2013)

Part 1. Describe in words in details the statistical analysis process you consider as appropriate to answer the researcher's claim: Subjects with preexisting cardiovascular symptoms who take subitramine are at increased risk of cardiovascular events while taking the drug. Clearly explain why you choose this statistical analysis process to investigate the question.

Part 2. The study included 9804 overweight or obese subjects with preexisting cardiovascular disease and/or type 2 diabetes. The subjects were randomly assigned to subitramine (4906 subjects) or a placebo (4898 subjects) in a double-blind fashion. The primary outcome was observed in 561 subjects in the subitramine group and 490 subjects in the placebo group. The data were analyzed through *StatCrunch* and the statistical analysis results are displayed below.

Hypothesis test results:

p_1 : proportion of successes for population 1
p_2 : proportion of successes for population 2
$p_1 - p_2$: difference in proportions
$H_0 : p_1 - p_2 = 0$
$H_A : p_1 - p_2 \neq 0$

Difference	Count1	Total1	Count2	Total2	Sample Diff.	Std. Err.	Z-Stat	P-value
$p_1 - p_2$	561	4906	490	4898	0.0143089425	0.0062489207	2.2898264	0.022

Answer the following questions according to the *StatCrunch* analysis results:

1. At the significance level of 5%, what can you conclude about the claim that subjects with preexisting cardiovascular symptoms who take subitramine are at increased risk of cardiovascular events while taking the drug? Report all the conclusions you can draw from the hypothesis test results in context. Explain clearly how you made your decision and came to your conclusion.

28. Can you conclude that taking subitramine causes a greater risk of cardiovascular events for those patients with preexisting cardiovascular symptoms? Why or why not?

Appendix M

Jessica’s Interview Question

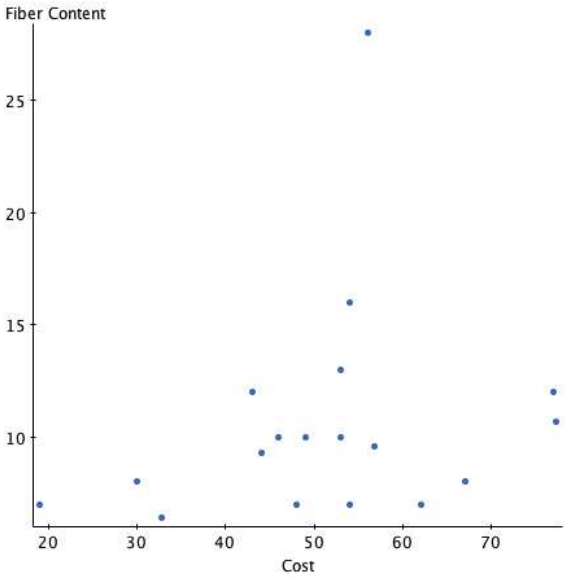
Scenario: Eighteen cereals were rated as having high fiber content by Consumer Reports. A health expert wants to study if fiber content (grams per cup) is linked to the cost (cents per cup) of the cereal. (Adapted from Peck, 2014)

Part 1. Describe in words in details the statistical analysis process you consider as appropriate to study the link between the fiber content and the cost of the cereal. Clearly explain why you choose this statistical analysis process to investigate the question.

Part 2. The health expert gathered the data and ran a simple regression analysis using *StatCrunch*. Answer the following questions according to the scatter plot and the analysis results displayed below:

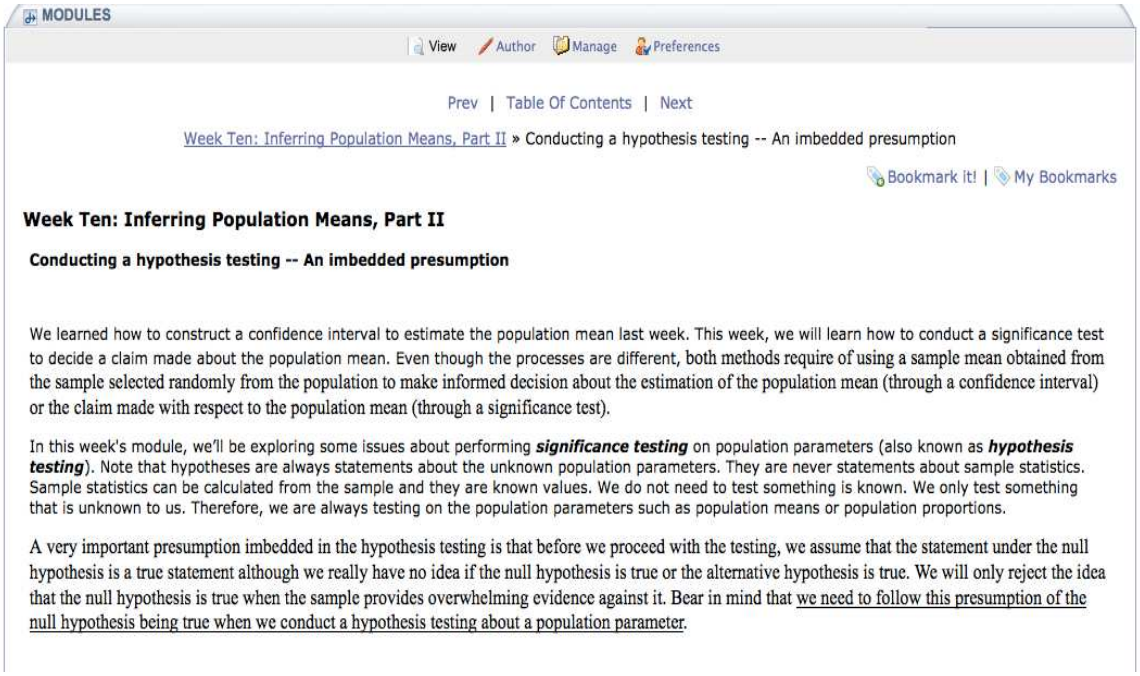
1. How strongly does cereal's fiber content correlate to the cost of the cereal? Clearly explain how you come up with your conclusion.

2. What would you advise the health expert if she wants to use the regression model to estimate the fiber content of the cereal when one of her clients is willing to buy a cereal that costs 60 cents per cup? Clearly explain how you come up with your advice.



Appendix N

Screenshot of Week Ten Module: Conducting a Hypothesis Test – An Imbedded Presumption



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Week Ten: Inferring Population Means, Part II » Conducting a hypothesis testing -- An imbedded presumption

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Week Ten: Inferring Population Means, Part II

Conducting a hypothesis testing -- An imbedded presumption

We learned how to construct a confidence interval to estimate the population mean last week. This week, we will learn how to conduct a significance test to decide a claim made about the population mean. Even though the processes are different, both methods require of using a sample mean obtained from the sample selected randomly from the population to make informed decision about the estimation of the population mean (through a confidence interval) or the claim made with respect to the population mean (through a significance test).

In this week's module, we'll be exploring some issues about performing ***significance testing*** on population parameters (also known as ***hypothesis testing***). Note that hypotheses are always statements about the unknown population parameters. They are never statements about sample statistics. Sample statistics can be calculated from the sample and they are known values. We do not need to test something is known. We only test something that is unknown to us. Therefore, we are always testing on the population parameters such as population means or population proportions.

A very important presumption imbedded in the hypothesis testing is that before we proceed with the testing, we assume that the statement under the null hypothesis is a true statement although we really have no idea if the null hypothesis is true or the alternative hypothesis is true. We will only reject the idea that the null hypothesis is true when the sample provides overwhelming evidence against it. Bear in mind that we need to follow this presumption of the null hypothesis being true when we conduct a hypothesis testing about a population parameter.

Appendix O

Weekly Module: Conducting a Hypothesis Testing, A Four-Step Process

We'll use the following four-step process to conduct the significance test: (adopted from Gould & Ryan, 2013).

1. **Hypothesize**: Set up the null hypothesis and the alternative hypothesis about the population parameter.
2. **Prepare & get ready to test**: Choose a significance level (*a*). Choose a test statistic appropriate for the test. Check and see if all the requirements needed are satisfied.
3. **Compute to compare**: Compute the test statistic. Find the *p*-value based on the test statistic.
4. **Make decision and Interpret**: Reject or not to reject the null hypothesis? What does this mean in context?

Example (***iTunes* Library**): We will continue with the *iTunes* lectures collection example. Recall that a random sample of 25 lectures was selected from the entire collection of a total of 59 Islamic lectures given by Shaykh Riyadh in Ms. Miao's *iTunes* library with a sample mean lecture length of 87.47 minutes and a sample standard deviation of 26.58 minutes. Conduct a hypothesis test that the population mean lecture length of the entire collection is longer than 60 minutes.

We'll follow the four-step process described above and fill in the details for each step.

1. **Hypothesize**: The ***null hypothesis*** indicates 'no difference than the claimed 60 minutes' while the ***alternative hypothesis*** states that the mean lecture length of the entire collection is longer than 60 minutes.

   H_o: $\mu = 60$

   H_a: $\mu > 60$

   Where m represents the mean lecture length of all the lectures collected in Ms. Miao's *iTune* library.

2. **Prepare and get ready to test**: The process of conducting a significance test always begins with a presumption that the statement under the null hypothesis is true. We then proceed with the test, using the sample evidence in a hope to reach to a decision that we could reject the presumption that the null hypothesis is true (reject H_o).

   Putting in context, we begin with an assumption that the population mean lecture length is 60 minutes. Next, we'll use the sample mean of 87.47 minutes as evidence in a hope to reach to a decision that we could reject the presumption. If this happens, we say that the sample mean is ***significant*** to conclude that the population mean lecture length is longer than 60 minutes. On the other hand, if we

fail to reject that the presumption is true then we say that the sample evidence is ***insignificant*** to conclude that the population mean lecture length is longer than 60 minutes.

Note that we use the sample mean as evidence in testing the claim of a population mean. Again, as mentioned before, this is because sample mean is an ***unbiased estimator*** to the population mean.

Choosing the significance level (a)

If we boil down the process of significance test, we see that the goal of conducting a significance test is to reject the null hypothesis (after we assume it is true). One issue comes up: What if we reject the null hypothesis while the null hypothesis is actually true? Don't we make a mistake? Yes, and we call this mistake a ***Type I error***.

We certainly don't want to make any mistakes during the hypothesis testing process. However, it is inevitable since we do not know whether the null hypothesis is true or not true. (Hint: The statements under the hypotheses are always about a population parameter. If we know the true value of a population parameter, there is no need to test it in the first place.) In fact, we have even no idea if we've made a mistake because we do not know the value of the parameter.

Even though we have no control over the truth-value of a parameter, we can certainly discuss the probability of making such a mistake. Fortunately, we can maintain the probability of making such a mistake (rejecting H_o when H_o is true) to as low as possible *without compromising the quality of the test*. The ***significance level*** (*a*) is the term we use to describe the probability of making such a mistake: Rejecting the null hypothesis when in fact the null hypothesis is true.

The significance level is prescribed prior to conducting the test to maintain the probability of making such a mistake (rejecting H_o when H_o is true, or simply, Type I error) to a low level possible *without compromising the quality of the test*. This can usually be achieved at $a = 5\%$. Putting in context, a significance level at 5% means the following:

The probability of making a false conclusion that the mean lecture length of all the lectures collected in Ms. Miao's iTunes library is longer than 60 minutes while in fact it is not is maintained at no more than 5%.

You might ask: Why not keep the probability of making a false conclusion about the null hypothesis at a level even lower than 5%? This is certainly a good suggestion. Unfortunately, a low probability of making a Type I error always leads to a high probability of making a Type II error (fail to reject the null

hypothesis when in fact the null hypothesis is false). If you recall, we mentioned that we would like to keep the probability of making a Type I error at a reasonably low level *without compromising the quality of the test*. The quality of the test is measured by the ***power of the test: 1 -*** β where β is the probability of making a Type II error.

When we decrease the probability of making a Type I error (α), the probability of making a Type II error (β) would go up, which leads to a decrease in 1 - β (the power of the test). As such, a researcher, generally, would not prescribe a low a, such as at 1%, unless he cannot afford making a Type I error. (That is, making a Type I error is considered to be so devastating that the researcher tries every possible way to avoid.)

Choose an appropriate test statistic

In addition to choosing a significance level (a), we need to choose an appropriate test statistic. To choose an appropriate test statistic means that we need to choose the *correct* sample estimator (that is, an *unbiased estimator*) and its sampling distribution. In testing the population mean, the sample estimator is the sample mean and the sampling distribution of the sample mean is a *Z* distribution. However, the standard error of the sample mean distribution requires the knowledge of population standard deviation, which, in most cases, is unknown. There is a need to use sample standard deviation to estimate the population standard deviation when calculating the standard error. Therefore, a modified *t* distribution would be used instead of the *Z* distribution.

In summary, the test statistic for testing the population mean when population standard deviation is unknown is

Checking the requirements

The last step in preparation for a hypothesis testing is to check the requirements needed for testing. As with the construction of confidence intervals, two requirements need to be checked:

a) Randomization: It is mainly about checking the sample selection. If the sample is selected randomly as a random sample, then the conclusion drawn from the hypothesis testing could be implied to the entire population. If the sample is not a random sample, then we cannot imply the conclusion to the entire population. Rather, the conclusion can only be made to that specific group of subjects.

b) Normality assumption: According to Central Limit Theorem, unless the population distribution of the variable is a symmetric distribution, our sample size needs to be large enough (usually at least 25) to ensure a symmetric

sample mean distribution. This normality assumption guarantees the acceptance of finding the test statistic: test *t* and use this result to continue the testing process.

In our example, the variable of lecture length of the entire collection does follow a normal distribution. Thus, the normality assumption is satisfied. This validates the choice of test *t* as a test statistic for conducting the test. As for the randomization assumption, the sample is selected at random. Therefore, later we could imply the hypothesis test results to Ms. Miao's entire collection of a total of 59 Islamic lectures given by Shaykh Riyadh.

3. **Compute to compare**: The validation of using test *t* as the test statistic has been established through the checking of the normality assumption. *StatCrunch* one sample *t* test gives the following test results:

   Hypothesis test results:
   μ : population mean
   $H_0 : \mu = 60$
   $H_A : \mu > 60$

Mean	Sample Mean	Std. Err.	DF	T-Stat	P-value
μ	87.47	5.316	24	5.167419	<0.0001

4. **Make decision and interpret**: From the displayed test results, we see that the hypothesis test is conducted to test that the population mean lecture length of the total 59 lectures given by Shaykh Riyadh is longer than 60 minutes (a right-tailed test). The standard error of 5.316 is calculated by dividing the sample standard deviation of 26.58 minutes by the square root of the sample size of 25. The degrees of freedom for the sample is the sample size minus one, or, 25 – 1 = 24. The test *t* is 5.17 and the *p*-value is less than 0.0001, which indicates a statistically significant result to reject the null hypothesis. That is, the sample mean lecture length of 87.47 minutes can be used as a significant piece of evidence that the mean lecture length of all the lectures given by Shaykh Riyadh in Ms. Miao's iTunes collection is longer than 60 minutes.

   Justification of the rejection rule: Reject the null hypothesis if *p*-value is less than or equal to α

   Let's understand the meaning of the *p*-value: *p*-value is similar to α in that they are both probabilities of making a Type I error (rejecting the null hypothesis when the null hypothesis is true). While α is a prescribed probability of making a Type I error, *p*-value is the actual probability of making a Type I error computed from the sample estimator. We use α as a guideline to decide if we could reject the null hypothesis by comparing the *p*-value with the α. So long as the probability of

making a Type I error computed from the sample evidence (*p*-value) is not greater than (less than or equal to) the prescribed probability of making a Type I error (α), we feel safe to reject the null hypothesis. This is because a Type I error is only made when we reject the null hypothesis.

On the other hand, if the computed probability of making a Type I error (*p*-value) is greater than the prescribed probability of making a Type I error (α), we feel that the chance of making a Type I error is too high if we still want to reject the null hypothesis. By not rejecting the null hypothesis, we avoid making a Type I error. Again, this is because a Type I error is only made when we reject the null hypothesis. However, by not rejecting the null hypothesis, we risk making a Type II error.

With a result of a *p*-value being less than 0.0001, we understand that the computed probability of making a Type I error using the sample mean lecture length of 87.47 minutes is almost 0. That is, the probability of rejecting that the mean lecture length is 60 minutes (the null hypothesis) when the mean lecture length is actually 60 minutes is almost 0. Knowing that the chance of making a Type I error is almost 0 (almost doesn't exist), we feel quite secure to reject the null hypothesis.

Appendix P

Weekly Discussion: Testing on a Population Mean

1. Select a random sample of 30 lectures from *Shaykh Riyadh iTunes lecture list (as of 2/10/13).* (Refer to the instructions given in last week's discussion forum to select your sample.) Share your sample data file with our *StatCrunch* class group.

2. Apply the four-step process as described in this module to conduct a hypothesis test that the population mean lecture length of the entire collection is longer than 80 minutes. Clearly describe each step in context. Post your *StatCrunch* one sample *t* test results on Etudes.

   Hypothesize:

   a) Set up two hypotheses and explain the meaning in context.

   b) Describe the Type I error and Type II error in context.

   Prepare & get ready to test:

   a) Select level of significance: What level of significance would you use? Why? Describe your alpha in context.

   b) Choose an appropriate test statistic: What is the appropriate test statistic for your test? Briefly explain why you choose this test statistic.

   c) Check the requirements: What are the requirements to check to conduct the test? Do they satisfy? Explain.

   Compute to compare:

   a) Conduct the appropriate test on *StatCrunch* and post the results here.

   b) Describe *p*-value in context.

   Make decision & Interpret:

   a) According to the statistical analysis results from *StatCrunch*, do you reject H_o? Why or why not? Explain in context.

   b) Is the sample evidence significant?

   c) Interpret your test decision in context.

Appendix Q

Project for Inferring Population Means

Instructions: There are three parts in this project. Each part of the project is described below. Please label each part of the project properly for readability. Include all the necessary graphs/charts in your response. Be sure the graphs and charts are displayed properly on the discussion forum. Please comment/critique at least two students' projects by providing meaningful and constructive suggestions. Respond to all the comments you receive.

Project Description:

Part I: Estimation through a Confidence Interval

[Refer to *W9-1* & *W9-2* discussions if needed.]

From your own data collection (data collected for Week 5 Project), select a quantitative variable on which you wish to estimate its population mean. (For example, from my *Facebook* data, I wish to estimate the mean number of mutual friends between all my friends and me on my *Facebook*. Therefore, I select the variable Mutual Friends for Part I of the project.)

1. Clearly describe the population parameter you wish to estimate in context. Based on the parameter you wish to estimate, define the variable in context. [The variable in context should be a short phrase (e.g. waiting time, distance, weight, etc.), not a question.]

2. According to the population parameter you wish to estimate, describe your population in context. Be as specific as possible.

3. Select a random sample of at least 30 observations from your data collection. Post your sample collection as a chart on Etudes. [Your chart should include the following two columns: Random numbers and the variable of interest.]

4. Describe the sample distribution of your sample selected in 3) in terms of the shape, center, and variation in context. Post the necessary charts/graphs produced from *StatCrunch* on Etudes.

5. Describe the sampling distribution of the sample mean based on your sample selection in terms of the shape, center, and variation in context. Justify your answer with a sound theorem.

6. Set up and carry out an appropriate statistical analysis procedure to estimate the population parameter you mentioned that you wish to estimate in 1). Discuss in as much detail as possible, including checking all the required conditions, to carry out the analysis procedure. Interpret the results obtained from the analysis procedure in context. Post *StatCrunch* statistical analysis results on Etudes.

Part II: Testing a Claim through Hypothesis Testing

[Refer to *W10-1* discussion if needed.]

From your own data collection (data collected for Week 5 Project), select a quantitative variable (different than the variable selected as in Part I) on which you wish to make a claim on its population mean. (For example, from my *Facebook* data, I wish to claim that the age of all my friends on *Facebook* is older than 40 years on average. Therefore, I select the variable Age for Part II of the project.)

7. Clearly describe your claim in context. Based on your claim, define your variable in context.

8. According to your claim, describe your population in context. Be as specific as possible.

9. Select a random sample of at least 30 observations from your data collection. Post your sample collection as a chart on Etudes. [Your chart should include the following two columns: Random numbers and the variable of interest.]

10. Set up and carry out an appropriate statistical analysis procedure to test the claim of the population parameter you mentioned that you wish to test in 7). Discuss in as much detail as possible, including checking all the required conditions, to carry out the analysis procedure. Interpret the results obtained from the analysis procedure in context. Post *StatCrunch* statistical analysis results on Etudes.

11. Based on your statistical analysis design, describe Type I error, Type II error, and *p*-value in context.

Part III: Comparing Two Population Means (Independent Samples)

[Refer to *W11-1* & *W11-2* discussions if needed.]

From your own data collection (data collected for Week 5 Project), select a quantitative variable on which you wish to compare the population means between two independent groups based on a qualitative variable collected in your data. (For example, from my *Facebook* data, I wish to compare the mean ages of all my friends on *Facebook* based on the gender. Therefore, I select the quantitative variable Age as the response variable and the qualitative variable Gender as the explanatory variable for Part III of the project.)

12. Clearly describe the population parameters you wish to compare in context. Be sure that the parameters are from two independent data sets. Based on what you wish to compare, define your variables in context.

13. According to the parameters you wish to compare, describe your populations in context. Be as specific as possible.

14. Select two independent random samples of <u>at least</u> 30 observations each from your data collection. Post your sample collections as a chart on Etudes. [Your chart should include the following four columns: Random numbers for Sample 1, variable of interest for Sample 1, random numbers for Sample 2, and variable of interest for Sample 2.]

15. Set up and carry out an appropriate statistical analysis procedure of your choice (constructing a confidence interval or conducting a hypothesis test) to compare the population parameters you mentioned that you wish to compare in 12). Discuss in as much detail as possible, including checking all the required conditions, to carry out the analysis procedure. Interpret the results obtained from the analysis procedure in context. Elaborate your interpretation by reflecting the benefits you get from the results. Post *StatCrunch* statistical analysis results on Etudes.

16. Explain to us why you chose the statistical analysis method over the other method in 15) to compare the population parameters.

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